

Optimizing a Menu of Multi-format Subscription Plans for Ad-Supported Media Platforms

Media content distribution has changed extensively in the past decade. Content, which was once distributed through traditional formats such as television, radio and print, is now available through contemporary digital formats with many possible versions, such as smartphone and tablet apps, and presence or absence of ads. Consequently, many media firms facing markets comprised of heterogeneous consumers with varying content consumption preferences are offering ‘menus’ of multi format-version subscription bundles for their consumers to choose from. Yet, little systematic model-based guidance exists for configuring and pricing menu options. Moreover, most media firms are ‘audience-building platforms’ that serve at least two distinct customer groups (content consumers and advertisers) with inter-related demands. Therefore, constructing a menu of content subscription bundles that maximizes total profit from both consumers and advertisers is a formidable challenge. This research proposes a theory-driven implementable model-based approach that can aid media platforms in addressing this challenge. The proposed approach is demonstrated for a U.S. newspaper and insights into profit maximizing menus under various business model and format strategies are provided.

Keywords: *Multi-channel, Menu design, Product line design, Platform firms, News media*

Introduction

Distribution of paid content to end-users by publishers, record companies and film studios has changed extensively in the past decade. Paid content, which was once distributed through traditional *formats* such as print, radio, or television is now also available through contemporary digital formats such as websites, smartphone apps and tablet apps. For instance, ESPN and Netflix content, which was previously accessible only on television, is now available via website and apps, with access through all digital devices (e.g., laptop, smartphone and tablet). Moreover, content within each format can now be delivered through multiple *versions*. For example, digital paywalls have helped newspapers to deliver digital news content via a ‘restricted access version’ (e.g., up to 20 free articles per month before charges) and an ‘unrestricted version’ (full access to subscribers). Likewise, music streaming websites such as Spotify are delivering digital music through a ‘version with advertising’ and a ‘version without advertising.’ Similar format-versions, e.g., free versus premium access to content delivered via specific formats, are offered by other content providers such as magazines (e.g., *TIME*, *McKinsey Quarterly*), academic books and journal publishers (e.g., *Springer*, *Harvard Business School Publishing*), radio broadcasting companies (e.g., *Sirius XM*), and online video streaming websites (e.g., *Hulu*). Hereafter, we refer to all such information or entertainment content providers as ‘media firms.’

While the proliferation of formats and versions is presenting advertising supported media firms with unprecedented opportunities to distribute and monetize content, practitioners lament the increasing complexity of determining the most profitable options (e.g., Newspaper Association of America 2012). For example, is it more profitable for a media firm to bundle access to all its formats and offer its consumers a single package (e.g., *Hulu*) or unbundle its

format-versions and offer each format-version or a subset of format-versions at a separate price (e.g., *New York Times*)? Moreover, recognizing that they face markets comprised of content consumers with heterogeneous content consumption preferences, media firms are now offering ‘menus’ of multi-format subscription bundles. However, little theoretical or practical guidance exists for how media firms should design their menus.

In general, designing a profit-maximizing menu for a heterogeneous customer group requires methodically evaluating several assortments of subscription bundles. While a formidable task in itself (Kohli and Sukumar 1990; Luo 2011; Venkatesh and Chatterjee 2006), this is even more complex for media firms because their business model typically involves not just one but at least two distinct customer groups with varying needs but inter-related demand functions. Specifically, most media firms are *audience building platforms* (Evans and Schmalensee 2007) that have ‘two-sided’ markets, i.e., serve two groups of customers with distinct preferences and interests: one group that is primarily interested in *consuming the content* produced by the firm, and the second group that *values the firm’s access to the first group*, namely, the advertisers (hereafter, we refer to such media firms as ‘media platforms’). Because one group’s demand affects the demand of the other group (also referred to as *cross market network effects or CMNEs*), strategies developed to maintain or grow the demand of one group without accounting for their repercussions on the demand of the other group are unlikely to maximize the media platform’s total profit from both groups (Sridhar et al. 2011). In particular, media platforms must account for demands of both content consumers and advertisers if they aim to design a profit-maximizing menu of multi-format subscription plans.

This menu-design problem, however, poses several significant conceptual and operational challenges for media platforms. First, these platforms have only recently begun

charging consumers for digital content. Moreover, the proliferation of formats through which digital content can be delivered (e.g., smartphones, tablets) now allows media platforms to offer many “new to the world” configurations of multi-format subscription plans. However, the novelty of such offerings implies there is little or *no previous data* on content consumers’ preferences and willingness to pay (WTP) for various new multi-format subscription plan options. Such data are essential for optimally configuring and pricing such plans. Second, determining the optimal menu that maximizes total aggregate profits of an advertising-supported media platform requires (i) estimates of content consumer *market potentials by format* under different possible menus; and (ii) estimates of inter-related aggregate content consumer and advertiser demand function *elasticities by format*. This is because advertisers pay for exposures to content consumers *by format* whatever be the particular menu or set of choices of multi-format subscription plans offered to content consumers. Third, firms need a mathematical model-based *approach or ‘optimizer’* for integrating the data on content consumers’ WTP for different plans with the aggregate format-level demand functions of content consumers and advertisers, and using this combined information to determine the total profit-maximizing menu of subscription plans from a very large number of possibilities.

To address these challenges, we propose a theory-driven implementable model-based approach for multi-format subscription menu design. Our approach comprises of three key steps (see Table 1). The first step entails assessing content consumers’ WTP for various multi-format plan configurations. The second step entails calibrating a two-sided market-level model of content consumer and advertiser ‘demands’ by format. The last step entails determining the profit maximizing menu of multi-format subscription plans using WTP information derived in the first step and the calibrated two-sided market demand model from the second step. The

proposed 3-step approach builds on classic consumer and economics theories such as: consumer utility maximization (McFadden 1986), WTP assessment (Kohli and Mahajan 1991), two-sided markets (Rochet and Tirole 2006) and market segmentation and consumer self-selection (Moorthy 1984). Methodologically, the three steps involve developing and using mathematical choice, econometric, and optimization models that we demonstrate in a case study involving a daily newspaper firm. Specifically, we collect and leverage primary data from the collaborating newspaper's content consumers (i.e., readers) as well as aggregate historical data on content consumer demand and advertising revenues by format to estimate the models and obtain inputs necessary to optimize subscription plan menus. Our proposed optimizer also allows us to determine optimal menus and predict total profits under various business models and format strategies of interest and relevance to the firm. As a result, we generate a number of useful insights into the merits of alternative business models and format strategies for our collaborating firm and other similar advertising supported media platforms.

<< Insert Table 1 about here >>

Our study offers several contributions to research aimed at integrating normative theory and practice in marketing (e.g., Fischer et al. 2011; Kannan et al. 2009; Kumar et al. 2013; Luo 2011). First, we offer a theory-based three-step approach for solving a topical, pressing and complex problem of designing an optimal menu of novel multi-format subscription plans for an advertising supported media platform. Second, we propose an optimizer that can effectively integrate *individual-level* WTP data for new subscription plans with *aggregate-level* archival data-based demand elasticities. Third, we present a novel mathematical programming model that determines a profit-maximizing subscription menu subject to accounting for the demands of both advertisers and consumers, as opposed to just considering one-sided market demand that

characterizes the traditional product line literature. Fourth, because our mathematical programming model is a complex discrete combinatorial optimization problem, we provide an efficient heuristic approach which can solve this problem in a reasonable amount of time and can be easily scaled up to handle more design alternatives and segments. Fifth, policy simulations enabled by our optimizer allow us to offer interesting insights into the efficacy of various media platform business models and format strategies. Sixth, empirical results from the estimation of the proposed models augment several findings previously documented in the two-sided platform, marketing and media economics literatures.

In the next section, we review and elaborate on our contributions relative to past research. We then detail how we executed our three-step approach in the context of a newspaper partner.

Literature Review

Various studies in the past marketing, economics and management science literatures provide helpful directions for solving the media platform's contemporary menu design problem. While a comprehensive review of these literatures is beyond the scope of this article, in this section, we will discuss literature relevant to our work and highlight the key points of departure.

First, our work is motivated by past literature on pricing in advertising supported two-sided markets. Research in this domain has primarily focused on illustrating: (a) how standard pricing norms designed under the one-sided market assumption change when *CMNEs* are incorporated (see Rochet and Tirole 2006 for a review), and (b) how pricing policies devised for monopolist platforms differ from those for competing platforms (see Armstrong 2006 for a review). While extant research in this domain provides helpful directions for modeling market-level demand functions of content consumers and advertisers, the majority of these papers are largely analytical in nature. The few studies that do empirically estimate demand models of two-

sided firms are either limited to cases where platforms offer products through a single format (e.g., Lambrecht and Misra 2015; Sridhar et al. 2011) or are aimed at explaining some observed market phenomenon (e.g., Pattabhiramaiah et al. 2014) as opposed to utilizing estimated models in a management decision aid for designing a menu of multi-format subscription plans.

Next, studies in bundling and versioning literatures have also added to our knowledge on optimal menu design. Beginning with Adams and Yellen (1976), scholars have sought to understand conditions when firms can benefit from a pure component, pure bundle, mixed bundle or a partial mixed bundle strategy in a *dual-product* (analogous to dual-format) setting. Venkatesh and Mahajan (2009) provide a comprehensive review of this literature. Similarly, scholars have also studied optimal bundling strategies in *dual-version* settings, where firms offer a high and a low quality version of the *same* format (e.g., Bhargava and Choudhary 2008; Bhargava et al. 2013). However, two limitations in these literatures motivate our work. First, existing bundling results are largely derived for one-sided markets where the goal of the firm is to design and price products (or formats) and versions for only one group of customers. Second, the need for analytical tractability has limited most bundling and versioning studies in two-sided markets to cases involving a monopolist firm producing only two product formats (e.g., Chao and Derdenger 2013; Derdenger and Kumar 2013) or two versions of a single product format (e.g., Bhargava et al. 2013). While the insights from these works certainly benefit media platforms with only two dominant formats or two versions of a format (e.g., 7 day and Sunday versions of the print newspaper format), the contemporary increase in the number of delivery formats (e.g., online, tablet, smartphone), and the number of versions per format (e.g., 7 day print, 3 day print, weekend print etc.), call for new model-based solutions for optimally configuring and pricing *multi-format* and *multi-version* offerings.

Last, research on product line design and pricing is also relevant to our work. Studies in this line of work have mainly focused on developing analytical procedures and heuristics that can leverage consumer preference data to determine optimal design and pricing of product lines. For example, Moorthy (1984) used ‘self-selection’ theory to analytically illustrate a theoretical model-based algorithm for how one-sided product firms can build multi-attribute product lines for markets comprised of heterogeneous consumer segments. Subsequently, more applied work using simulated data by Kohli and Sukumar (1990) has demonstrated the effectiveness of various heuristics for designing multi-attribute product line offerings using conjoint analysis. While this literature stream offers valuable insights into modeling consumers’ plan selection process and using conjoint data to design and price product lines, past research is largely limited to one-sided markets. More importantly, the product-line design heuristics proposed so far do not offer any guidance for integrating individual WTPs for new subscription plans with aggregate-level transaction data in order to determine the profit maximizing menu.

In summary, our work is differentiated from all past research in the three streams of relevant literature because it addresses a new but prevalent practical problem facing contemporary media platform firms - the optimal design of a menu of multi-format multi-version offerings in a two-sided market, with an approach that effectively integrates individual and aggregate-level data available to an ad-supported media platform.

Application

Institutional Context

Our research was conducted in collaboration with a prominent U.S. West Coast daily newspaper firm. Like many daily newspapers in the US, this firm is effectively a local monopoly (Sokullu 2015) in a specific city-centered geographic region with three main revenue sources at

the time we commenced our collaboration: print subscriptions, print advertising, and digital advertising. Moreover, the firm derived 90% of its total revenue from subscriptions to the ‘Seven day’ and ‘Sunday only’ versions of the print format. Historically, the newspaper had not charged its content consumers (i.e., readers) for accessing digital content. However, declining print advertising revenues had forced it to consider charging consumers for access to digital content, currently available on their website and planned to be made available via smartphone and tablet apps. Consequently, the firm’s goal, when we began our research, was to develop a profit maximizing menu of multi-format subscription plans. Below, we describe how we accomplished this objective following the steps outlined in Table 1.

Step 1: Estimating Content Consumers’ WTP for Multi-format Subscription Plans

Model: If historical transaction data for all newspaper versions in print and digital formats were available, we could potentially estimate content consumer preferences and price sensitivity across formats and versions using econometric time-series methods. However, because the collaborating newspaper has never previously monetized its digital formats, useful archival data are not available to estimate preferences. Therefore, we rely on a choice-based conjoint (CBC) approach (Rao 2011) to measure content consumers’ preferences for various formats and, subsequently, use the preferences to compute WTP for various plan combinations.

More specifically, we consider a CBC study setting with N subjects, Q choice sets and G subscription plans, where a reader i's utility function can be stated as follows:

$$U_i(\mathbf{x}_{gq}, p_{gq}, \mathbf{z}_{gq}) = (\mathbf{x}'_{gq}\beta_{ix} + p_{gq}\beta_{ip} + \mathbf{z}'_{gq}\beta_{iz}) + \varepsilon_{igq} \quad (1)$$

where

x_{gq} = a vector of 1s and 0s representing multi-format versions available in plan g and choice set q

p_{gq} = weekly subscription price of plan g in choice set q

z_{gq} = a vector representing interactions between the formats

- β_{ix} = a vector of parameter coefficients (part-worths) corresponding to format-version x for reader i
- β_{ip} = parameter coefficient (part-worth) of price p for reader i
- β_{iz} = a vector of parameter coefficients (part-worths) corresponding to the interactions between the formats
- ε_{iq} = random component of reader i 's utility

The additively separable model specification in Equation (1) is in line with the literature that models consumer utility as linear combination of attribute preferences (Jedidi and Jagpal 2009; Luo et al. 2007; McFadden 1986; Rao 2011). Additionally, following recent research that demonstrates complementary and substitution effects between print and digital formats (e.g., Koukova et al. 2008), we include latent interactions effects between formats (i.e., β_{iz}).

Next, the multi-format versions and price levels are all coded as effects-type discrete variables (i.e., the part-worths of all levels within an attribute add to 0) and the part-worths are assumed to follow a multivariate normal distribution. Subsequently, we model the probability that reader i chooses plan g in choice set q using a standard logit formulation:

$$Pr_{iqg} = \frac{\exp(\mathbf{x}'_{gq}\beta_{ix} + p_{gq}\beta_{ip} + \mathbf{z}'_{gq}\beta_{iz})}{\sum_{g'=1}^G \left[\exp(\mathbf{x}'_{g'q}\beta_{ix} + p_{g'q}\beta_{ip} + \mathbf{z}'_{g'q}\beta_{iz}) \right] + \exp(\alpha_i)}, \forall i \in I \text{ and } \forall q \in Q \quad (2)$$

where α_i is the constant term representing the utility of the no-choice option for reader i .

We use standard hierarchical Bayesian (HB) estimation available in the Sawtooth software (see a technical note on HB CBC from Sawtooth 2009) to obtain part-worth estimates of various formats for each respondent.

Upon obtaining individual part-worths for content consumers, we use a point estimation technique described by Kohli and Mahajan (1991) to derive WTP of a plan configuration j using the part-worths of format versions (β_{ix}), price (β_{ip}) and the no-choice option (α_i) for a content consumer i . The prescribed technique is a 'piece-wise' linear approach that treats WTP as a

maximum price at which the reader is indifferent between subscribing and not-subscribing to a newspaper offering. This can be represented as follows:

$$U_{ij|-p} + U_i(p) \geq \alpha_i + \tilde{\varepsilon} \quad (3)$$

where $U_{ij|-p}$ represents the total utility of the plan configuration j excluding reader i 's utility of price. $U_i(p)$ is the utility of a price point p , α_i is reader's utility of the status quo or the no-choice option and $\tilde{\varepsilon}$ is an arbitrary positive number used to round the price "p" to the nearest 25 cent. The challenge here is to find the right price, p , for a reader i such that the sum of her utility for that price ($U_i(p)$) and her utility for the plan configuration ($U_{ij|-p}$) is equal to the utility of the no-choice option (α_i). We refer to price 'p' as the WTP of reader i for the plan configuration j . The specifics of the algorithm used to compute WTP are outlined in Web Appendix W1. The resulting WTP matrix is a critical input to Step 3 in our outlined approach.

Application: To estimate our choice model and derive WTPs, we recruited subjects from two sources: (a) an online intercept on the home page of the newspaper firm's website, and (b) a research pool comprised of the collaborating firm's readers who had expressed interest in participating in the firm's research activities. Subjects were screened based on their frequency of news consumption through the newspaper's media formats (i.e., print and digital) and smartphone and tablet device ownership. This recruitment process ensured that survey respondents were knowledgeable about the key design elements (i.e., format-versions) in the conjoint survey. Our final sample comprised 1144 readers (see Web Appendix W2 for descriptives of the sample).

Each CBC profile consisted of four key design attributes and a price attribute. The design attributes comprised news delivery formats being considered by the collaborating newspaper, namely: (a) print, (b) website, (c) smartphone app, and (d) tablet app. A group of managers from

the newspaper's circulation and research departments iteratively reviewed and modified the formats and their definitions until they reached consensus. Each format had distinct versions (or 'levels' in conjoint analysis terminology). The print format had three levels, specifically, two possible 'versions' i.e., home delivery of print copies (i) on all 7 days of a week; (ii) on just Sunday, and a (iii) 'print delivery of news unavailable' option. The website format had five levels, specifically, four possible 'versions' i.e., (i) unlimited online access (where content on the website is optimized for viewing on any device, e.g., computer, smartphone and tablet), (ii) limited free online access (to only 20 stories per week) where content is optimized for viewing on any device; (iii) unlimited online news access on a smartphone device, (iv) limited free access to only 20 stories per week on a smartphone device, and a (v) 'access to online news unavailable' option. Next, both smartphone app and tablet app formats had two levels each: 'unlimited access to news content via the respective device' and 'device delivery of news is unavailable.'

To check if the range of price levels selected affects respondents' evaluation of format-versions, we created two versions of the conjoint survey. The two survey versions only differed in the price points assigned to plan alternatives in choice tasks and were randomly assigned to respondents. The managers picked weekly subscription price levels: \$0.99, \$1.99, \$3.49, \$4.99 and \$6.99 for the first version and \$1.49, \$3.49, \$4.99, \$6.99 and \$8.99 for the second version.

The stimuli (i.e., profiles) for the CBC conjoint analysis section of the survey were generated using OPTEx macro in SAS. Design constraints were imposed such that the plan configurations presented in a choice task were managerially relevant. Subsequently, a saturated fractional factorial design that met three efficient experimental design criteria: minimal overlap in plan configurations, level balance, and orthogonality, was obtained using the OPTEx macro. The final conjoint survey comprised 13 choice tasks with three plan combinations and a no

choice option per choice task. Two additional choice tasks were added to assess predictive validity of the estimated part-worths. To control for order effects, plans within a choice task as well as the choice tasks themselves were randomized. The stimuli were pretested on 17 employees at the collaborating newspaper firm to assess face validity of the choice tasks and cognitive load. Some changes with respect to wording of the attributes and levels were suggested, which were subsequently incorporated into the final design. Finally, we incentive-aligned subjects by repeatedly informing them at multiple phases of the survey that they will be entered into a drawing to win one of ten \$250 rewards and, if they won, their total reward would be *split* between dollar amount (i.e., cash reward) and a three-month subscription to a plan that reflected their preferences in choice tasks.¹

A-priori segmentation information was obtained from the collaborating newspaper. Once in every three years, the newspaper firm employs a reputable third party research company to identify segments among its existing readers in the NDMA. The ensuing segment information is used by the newspaper firm for guiding its marketing efforts. In the most recent study conducted in 2014, the research firm had identified 22 questions comprising media preferences, news and information needs and demographic information to segment the NDMA. Using k-means clustering on these 22 variables, the research firm had uncovered 7 “strategic segments” (see Web Appendix W3 for details). The cluster weights assigned to the 22 variables for each segment were shared by the firm to help us determine segment memberships of survey participants.

¹ We believe that splitting the total reward into monetary and non-monetary components encourages truth telling among the survey respondents because preferring a plan that is more (less) expensive, when the respondent is truly interested in another plan, would not only result in less (more) monetary compensation but would also result in a three-month subscription to plan that the respondent doesn’t truly like. For example, a respondent that chooses a ‘print + digital’ plan, when she truly prefers ‘digital only’ plan, will get a smaller dollar reward (because, as per the study’s design, ‘print + digital’ plan is more expensive than the ‘digital only’ plan) and a three-month subscription to a plan that the respondent doesn’t like. Therefore, the respondent will be better off stating her true preference.

The ‘CBC/HB’ module in the Sawtooth software was used to estimate part-worths. To improve fit, we included segment membership information in the Gibbs sampler (Allenby et al. 1995). 20,000 iterations were used to obtain stable part-worths with a burn-in of 10,000 iterations to achieve convergence. The algorithm converged with excellent fit statistics. The percent certainty was over 75%, the root likelihood was over 70%, and the RMS was less than 4 for both the versions. Average part-worths of various levels by reader segments and survey versions are presented in Table 2. Out-of-sample predictions were performed to assess the robustness of the part-worths. The results demonstrate excellent first-choice hit rates for both holdout tasks in both survey versions (74% and 77.6% in version 1 and 83.4% and 86 % in version 2). Additionally, to ensure the reliability of part-worths, we performed several other robustness checks, which we outline in Web Appendix W4.

A total of 59 distinct plan combinations are feasible with the design attributes and their corresponding levels. WTP was computed for every plan combination and individual using the algorithm outlined in Web Appendix W1. Subsequently, the values were averaged by segment to obtain two 7 x 59 matrices of WTPs (one for each version). Next, a nonparametric Kolmogorov-Smirnov test for 2 samples confirmed that the distribution of WTP values for respective plan configurations are identical across segments in both versions of the conjoint survey. Specifically, at 95% (99%) confidence level, 83.1% (92.4%) of plan configurations were similarly distributed. Because of this reasonable evidence of similarity in WTP distributions, data from both versions of the conjoint survey were merged to form one 7 x 59 WTP matrix. This matrix of WTP estimates is a critical input for Step 3 in our outlined approach.

<< Insert Table 2 about here >>

Step 2: Estimating Two-sided Demand Functions of Content Consumers and Advertisers

Model: In this step, we propose and subsequently estimate a two-sided aggregate model of demands by format of content consumers and advertisers. In specifying these demand functions, we incorporate five key effects:

(i) *Cross market network effects (CMNEs)*: First, in advertising-supported media platforms, demand from readers may affect the demand from advertisers and vice-versa (Armstrong 2006; Rochet and Tirole 2006).

(ii) *Marketing investment effects*: Second, reader demand is typically affected by news quality (Chen et al. 2005) and distribution investments (Mantrala et al. 2007) and advertising demand is affected by sales force investments (Sridhar et al. 2011).

(iii) *Installed base and carryover effects*: Third, advertising and reader demands are also affected by consumers who have subscribed to the newspaper's offering (i.e., content or ad space) in the previous period (i.e., installed bases) through a variety of social effects (Narayanan and Nair 2013), word of mouth, tradition, habit persistence, and past experience (Erdem et al. 2003).

(iv) *Cross format effects*: Fourth, past research has shown that the introduction of print and digital formats for content delivery may have complementary or substitution effects on reader demand (Chyi and Lasorsa 2002; Koukova et al. 2012), which could subsequently affect advertisers' allocation of their budgets across different formats (Sridhar and Sriram 2015).

(v) *Market potentials' effects*: Fifth, content consumers' demand is affected by changes in their market potentials due to factors such as population growth, government reforms, technological advances, digital literacy and employment opportunities. In turn, changes in the number of potential content consumers in the NDMA can make the NDMA more or less 'attractive' for advertisers, thereby affecting advertising demand (Talukdar et al. 2002).

We incorporate these five effects in the following 4-equation response model system:

$$PA_t = (1 + PA_{t-1})^{\beta_{PA}} (PR)_{t-1}^{\beta_{RP}} (1 + OA_t)^{\beta_{OAPA}} (PAMM)_{t-1}^{\beta_{PAMM}} (PMP)_t^{\beta_{PAMP}} (e_{1t})^{\alpha_1} \quad (4)$$

$$PR_t = (1 + PR_{t-1})^{\beta_{PR}} (1 + PA_{t-1})^{\beta_{AP}} (1 + OR_t)^{\beta_{ORPR}} (PRMM)_{t-1}^{\beta_{PRMM}} (PMP)_t^{\beta_{PRMP}} (e_{2t})^{\alpha_2} \quad (5)$$

$$OA_t = (1 + OA_{t-1})^{\beta_{OA}} (OR)_{t-1}^{\beta_{RO}} (1 + PA_t)^{\beta_{PAOA}} (OAMM)_{t-1}^{\beta_{OAMM}} (OMP)_t^{\beta_{OAMP}} (e_{3t})^{\alpha_3} \quad (6)$$

$$OR_t = (1 + OR_{t-1})^{\beta_{OR}} (1 + OA_{t-1})^{\beta_{AO}} (1 + PR_t)^{\beta_{PROR}} (ORMM)_{t-1}^{\beta_{ORMM}} (OMP)_t^{\beta_{ORMP}} (e_{4t})^{\alpha_4} \quad (7)$$

where,

PA_t, OA_t	Print and digital advertising demand at time period t
PR_t, OR_t	Print and digital reader demand at time period t
$PAMM, OAMM$	Marketing investments that affect print and digital <i>advertiser</i> demand
$PRMM, ORMM$	Marketing investments that affect print and digital <i>reader</i> demand
PMP, OMP	Number of potential print and digital readers in the NDMA
β_{PA}, β_{OA}	Installed base effects of print and digital advertiser demand
β_{PR}, β_{OR}	Installed base effects of print and digital reader demand
β_{RP}, β_{RO}	CMNE of reader demand on advertiser demand in print and digital formats
β_{AP}, β_{AO}	CMNE of advertising demand on reader demand in print and digital formats
$\beta_{PAMM}, \beta_{OAMM}$	Effects of marketing investments on advertiser demand in print and digital formats
$\beta_{PRMM}, \beta_{ORMM}$	Effects of marketing investments on reader demand in print and digital formats
$\beta_{OAPA}, \beta_{PAOA}$	Cross format effects of advertiser demand in print and digital formats
$\beta_{ORPR}, \beta_{PROR}$	Cross format effects of reader demand in print and digital formats

The multiplicative model specification of these demand equations extends the one adopted by Sridhar et al. (2011) to multiple formats and captures two important real-world characteristics of the newspaper business. First, it accounts for the nonlinear relationship between key independent variables and the dependent variable. For example, we are able to specify that an increase in marketing-mix will increase advertising revenue at a diminishing rate. Next, it also allows for implicit interactions among independent variables. Additionally, we also incorporate another real-world characteristic where advertiser demand is 0 when reader demand is 0 (but not vice-versa) by specifying $(1+PA)$ and $(1+OA)$ in equations 5 and 7.

Application: To calibrate the proposed market response model, we use nine years of monthly transaction data from the collaborating newspaper. We operationalize print and digital advertising demand using advertising revenue because it comprehensively captures several important ad features that are regularly scrutinized by ad managers while determining their ad budgets such as: advertising rates, number of advertising inches, the shape of the advertisement,

location of the advertisement on the page, frequency of appearance, and location of the ad within a content area. Next, we operationalize print reader demand using total number of newspaper subscriptions and digital reader demand using total number of unique visitors to the newspaper's website from the NDMA. It is worth noting that we use penetration rate (PR_{t-1} , OR_{t-1}) to capture the CMNEs of reader demand on advertiser demand in Equations (4) and (6) because managers noted that penetration rate provides advertisers with a better sense of market coverage than the raw reader demand. We derive print and online penetration rates as follows:

$$\text{Print Penetration Rate} = \frac{(\text{Print subscriptions} * \text{Pass along rate})}{\text{PMP}} \quad (8)$$

$$\text{Digital Penetration Rate} = \frac{\text{Unique visitors to newspaper's website from the NDMA}}{\text{OMP}} \quad (9)$$

where pass-along-rate is the number of people who see each issue, including the subscriber and every other person her copy is passed to before it is discarded. We obtain PMP and OMP data from a third party firm that was hired by the collaborating newspaper to provide market intelligence. Last, the collaborating platform has one sales force selling both print and digital ad space.

The time-series plots of readership volume and advertising revenue indicated that the two variables exhibit strong trend, seasonality, and cyclicity. Additionally, the effect of recession was also observed in the data (see Web Appendix W5 for descriptives of all variables used in our analyses). To account for these effects, we log-transformed Equations (4) through (7) and augmented the equations with trend, seasonality, cyclicity and recession variables:

$$\begin{bmatrix} \ln(PA_t) \\ \ln(PR_t) \\ \ln(OA_t) \\ \ln(OR_t) \end{bmatrix} = \begin{bmatrix} \beta_{PA} \ln(1 + PA_{t-1}) + \beta_{RP} \ln(PR)_{t-1} + \beta_{OAPA} \ln(1 + OA_t) + \beta_{PAMM} \ln(PAMM)_{t-1} \\ \beta_{PR} \ln(1 + PR_{t-1}) + \beta_{AP} \ln(1 + PA_{t-1}) + \beta_{ORPR} \ln(1 + OR_t) + \beta_{PRMM} \ln(PRMM)_{t-1} \\ \beta_{OA} \ln(1 + OA_{t-1}) + \beta_{RO} \ln(OR)_{t-1} + \beta_{PAOA} \ln(1 + PA_t) + \beta_{OAMM} \ln(OAMM)_{t-1} \\ \beta_{OR} \ln(1 + OR_{t-1}) + \beta_{AO} \ln(1 + OA_{t-1}) + \beta_{PROR} \ln(1 + PR_t) + \beta_{ORMM} \ln(ORMM)_{t-1} \end{bmatrix}$$

$$+ \begin{bmatrix} \beta_{PAOA} \ln(OA)_t + \beta_{PAMP} \ln(PMP)_t \\ \beta_{PROR} \ln(OR)_t + \beta_{PRMP} \ln(PMP)_t \\ \beta_{OAPA} \ln(PA)_t + \beta_{OAMP} \ln(OMP)_t \\ \beta_{ORPR} \ln(PR)_t + \beta_{ORMP} \ln(OMP)_t \end{bmatrix} + \begin{bmatrix} \gamma_{\tau 1} \tau_t + \gamma_{s 1} s'_t + \gamma_{c 1} c'_{t1} + \gamma_{r 1} r'_t \\ \gamma_{\tau 2} \tau_t + \gamma_{s 2} s'_t + \gamma_{c 2} c'_{t2} + \gamma_{r 2} r'_t \\ \gamma_{\tau 3} \tau_t + \gamma_{s 3} s'_t + \gamma_{c 3} c'_{t3} + \gamma_{r 3} r'_t \\ \gamma_{\tau 4} \tau_t + \gamma_{s 4} s'_t + \gamma_{c 4} c'_{t4} + \gamma_{r 4} r'_t \end{bmatrix} + \begin{bmatrix} \tilde{\epsilon}_{1t} \\ \tilde{\epsilon}_{2t} \\ \tilde{\epsilon}_{3t} \\ \tilde{\epsilon}_{4t} \end{bmatrix} \quad (10)$$

where, γ_{τ} captures the effect of the linear trend variable τ . Similarly, γ_{s} captures the year end seasonality effect of the thanksgiving and Christmas holiday season (s'_t), where s'_t is defined as:

$$s'_t = \begin{cases} 1, & \text{if } t = 11, 12, 23, 24, \dots, 107, 108 \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

Likewise, γ_r captures the effect of recession (r'_t), where r'_t is defined as:

$$r'_t = \begin{cases} 1, & \text{if } t \text{ is a month in the recessionary period as defined by NBER} \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

Lastly, short-term cyclicity in each of the 4 dependent variables was extracted using the well-known Hodrick and Prescott filter (Hodrick and Prescott 1997).

Note that the error terms in the vector $(\tilde{\epsilon}_{1t} \quad \tilde{\epsilon}_{2t} \quad \tilde{\epsilon}_{3t} \quad \tilde{\epsilon}_{4t})'$ from Equation (25) pose two unique estimation challenges. First, the error terms could be *contemporaneously correlated* within a time period. Second, the error terms could also be *serially correlated*. Therefore, to determine whether there is dependency among error terms, we estimated Equation (25) using OLS and SUR techniques. Subsequently, we performed a Hausman (1978) specification test to examine whether there is a systematic difference between the parameter estimates obtained using both regression techniques. A highly significant chi-square test statistic (190.97 (37), $p < 0.01$) established the presence of systematic differences in the parameter estimates. Consequently, we used SUR in the rest of the analysis. To test and account for serial correlation, we followed Jacobson (1990) and estimated the response model with multiple lagged error specifications. We observed that the model fit deteriorated with the addition of error lags > 1 . Hence, we settled with a response model with a single error lag specification.

Next, to ensure parsimony and fidelity in model estimation, we evaluated a series of nested models to identify a model that yields a good model fit, low autocorrelation and high forecast accuracy. We used BIC to assess model fit and the Durbin-Watson statistic to evaluate autocorrelation within error terms. Forecast accuracy was examined using MAPE and MAD from the hold-out sample. Specifically, for each nested model, parameter estimates derived using the estimation sample ($n = 77$) were used to forecast the dependent variable in the holdout sample ($n = 30$). Subsequently, MAPE and MAD of the 30 forecasts were used to gauge predictive accuracy of the model. Table 3 summarizes the features of various nested models and diagnostics from the estimation of various model specifications. Model 5 outdid all models with the smallest BIC (-1755.81), smallest MAPE (1.560%) and smallest MAD (0.23) and no autocorrelation ($DW = 2.25$). Additionally, Model 5 also demonstrates satisfactory fit (see Figure 1). Moreover, it performed better than the model with cross-format effects (BIC = -1748.611). Therefore, we dropped the variables that captured cross-format effects and retained results from Model 5 for further analysis.

<< Insert Table 3 and Figure 1 about here >>

To validate the robustness of parameter estimates in Model 5, we performed numerous additional checks (see Web Appendix W6-A for a complete list). For instance, we performed the Phillip-Perron test² to check for stationarity of error terms in the vector $(\tilde{\varepsilon}_{1t} \ \tilde{\varepsilon}_{2t} \ \tilde{\varepsilon}_{3t} \ \tilde{\varepsilon}_{4t})'$. Results confirmed that the errors were stationary. Next, to we determine exogeneity of the independent variables using Engle, Hendry and Richard's (1983) approach. Analysis indicated that marketing mix variables are weakly exogenous (see Web Appendix W6-B for details), hence a precise specification was not necessary.

² An Augmented Dicker-Fuller (ADF) test can be used to check for stationarity in error terms. However, heteroskedasticity in the error terms could bias the results of the ADF test.

It is worth noting that the key parameter estimates from the econometric analyses of content consumer and advertiser demands (presented in Table 3) also shed light on some interesting patterns, which validate and augment previous marketing literature:

- (a) First, we find *reinforcing* (as opposed to countervailing) CMNEs between readers and advertisers in *both print and digital formats*. This finding augments previous literature that demonstrates this pattern in the *print* format (Sridhar et al. 2011).
- (b) Second, the analysis confirms a robust positive association between product quality and readership in print as well as digital formats. This finding augments previous work on the effect of product quality on readership in the *print format* (Mantrala et al. 2007).
- (c) Third, while advertising revenue at the collaborating firm declined during the economic downturn, the newspaper's subscription numbers remained unaffected. This is counterintuitive because scholars have assumed that consumers generally cut spending during recession (Srinivasan et al. 2011).
- (d) Fourth, digital advertising revenues are more elastic to sales force investments than print advertising revenues. This result validates previous literature on sales force elasticity in traditional selling environments (Albers et al. 2010).
- (e) Fifth, we find that advertisers are more elastic to readership than readers are to advertising.
- (f) Sixth, consistent with the literature that documents "service" (e.g., distribution) as one of the key factors affecting likelihood of re-patronage (Tokman et al. 2007), we find that investments in distribution indeed have a positive elasticity on content consumer demand. However, distribution elasticity is smaller than quality and sales force elasticities.

In summary, our calibrated market response model demonstrates high forecast accuracy and consistency with the previous literature. Hence, we use it in Step 3 of our approach.

Step 3: Computing a Profit Maximizing Menu of Multi-format Subscription Plans

In the last step, we propose a static optimization model ('optimizer') that integrates WTP estimates for various plan configurations from Step 1, and the calibrated market response model from Step 2 in a mathematical program to determine a profit-maximizing menu of multi-format subscription plans. We implement this math program using a novel heuristic that efficiently and

rapidly determines the optimal solution from the very large number of possibilities. Figure 2 demonstrates the logical flow of our optimizer.

<< Insert Figure 2 about here >>

Optimizer overview: The primary objective of the newspaper is to design an optimal menu of subscription plans that maximizes its total profits derived from both content consumers and advertisers. Therefore, to evaluate the total profits from every possible plan within a given menu, the optimizer first determines the plan selections of each content consumer segment based on their WTPs obtained in Step 1 of our approach (Table 1). Then, the optimizer will compute the content consumers' market potential by each format by aggregating the market-level demand of all segments that picked a plan which contains access to the corresponding format. These potentials serve as inputs to the calibrated aggregated content consumer demand and advertising revenue functions obtained in Step 2, leading to forecasts of the content consumer demand and advertising revenue for the subscription menu in question. Subsequently, the optimizer uses the segment proportions of the market to break down the content consumer demand forecasts by segment to obtain segment-level demand forecasts. Then, for each content consumer segment, the optimizer will multiply their corresponding demand forecasts by format with the price of the plan chosen by that segment to obtain the subscription revenues from that segment. As a result, the total profits from subscription as well as advertising revenues under the menu being evaluated are derived by multiplying content consumer and advertiser revenues with corresponding gross margins. The optimizer executes this procedure for various menu configurations determined by our heuristic to find the total profit-maximizing menu.³

³ It is worth noting that the optimizer we propose is static in nature. That is, it does not capture stochastic nature of content consumers' WTP and content consumers' and advertisers' demands. This model characteristic is in line with the real world observation that media platforms do not change their menus frequently. Several marketing, sales,

Optimization Model: We now present the mathematical programming model followed by an explanation of each equation.

$$\text{Maximize } \sum_j B_j (PF_j) + (PA_t + OA_t) * M_a \quad (13)$$

$$\text{s.t. } \delta_{kj} = \begin{cases} 1, & \text{if } S_{kj} \geq \max_{i \in J} \{B_i * S_{ki}\} \cap S_{kj} \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad \forall j, k \quad (14)$$

$$S_{kj} = RP_{kj} - P_j \quad \forall j, k \quad (15)$$

$$\sum_{j \in J} \delta_{kj} \leq 1 \quad \forall k \quad (16)$$

$$X_j = \sum_{k=1}^K \max\{N_k^p * \delta_{kj} * \lambda_j^p, N_k^o * \delta_{kj} * \lambda_j^o\} \quad \forall j \quad (17)$$

$$MP = \sum_{j \in J} X_j * \lambda_j^p \quad (18)$$

$$MO = \sum_{j \in J} X_j * \lambda_j^o \quad (19)$$

$$PA_t = (1 + PA_{t-1})^{\beta_{PA}} (PR)_{t-1}^{\beta_{RP}} (1 + OA_t)^{\beta_{OPA}} (PAMM)_{t-1}^{\beta_{PAMM}} (MP)_t^{\beta_{PAMP}} (e_{1t})^{\alpha_1 + Z_1} \quad (20)$$

$$PR_t = (1 + PR_{t-1})^{\beta_{PR}} (1 + PA_{t-1})^{\beta_{AP}} (1 + OR_t)^{\beta_{ORPR}} (PRMM)_{t-1}^{\beta_{PRMM}} (MP)_t^{\beta_{PRMP}} (e_{2t})^{\alpha_2 + Z_2} \quad (21)$$

$$OA_t = (1 + OA_{t-1})^{\beta_{OA}} (OR)_{t-1}^{\beta_{RO}} (1 + PA_t)^{\beta_{PAOA}} (OAMM)_{t-1}^{\beta_{OAMM}} (MO)_t^{\beta_{OAMP}} (e_{3t})^{\alpha_3 + Z_3} \quad (22)$$

$$OR_t = (1 + OR_{t-1})^{\beta_{OR}} (1 + OA_{t-1})^{\beta_{AO}} (1 + PR_t)^{\beta_{PROR}} (ORMM)_{t-1}^{\beta_{ORMM}} (MO)_t^{\beta_{ORMP}} (e_{4t})^{\alpha_4 + Z_4} \quad (23)$$

$$PF_j = \sum_{k=1}^K \max\{PR_t * M_{pr} * \lambda_j^p, OR_t * M_{or} * \lambda_j^o\} * P_j * \delta_{kj} * \varphi_k \quad \forall j \quad (24)$$

$$B_j \in (0, 1), \delta_{kj} \in (0, 1) \quad (25)$$

Notation

J	= Index of subscription plans, $j = 1, \dots, J$
k	= Index of customer segments, $k = 1, \dots, K$
N_k^p	= Number of print readers in a customer segment k in the NDMA
N_k^o	= Number of digital readers in a customer segment k in the NDMA
RP_{kj}	= Reservation price of the k th segment for the j th subscription plan
λ_j^p	= 1 if the j th subscription plan has a print format, 0 otherwise
λ_j^o	= 1 if the j th subscription plan has a digital format, 0 otherwise
φ_k	= Proportion of segment k in the newspaper's NDMA
M_a	= Margin on print and digital advertising revenue
M_{pr}, M_{or}	= Margins on print and digital subscription revenues

finance, accounting and IT activities hinge on the composition and price of the content subscription plans put forth by the platform. Therefore, media platforms typically refrain from modifying their subscription offerings frequently.

Decision Variables

- P_j = Price assigned to bundle j , $P = (P_1, \dots, P_j)$
 B_j = 1 if the newspaper is offering the j^{th} subscription plan, 0 otherwise

Auxiliary Variables

- PF_j = Subscription profit from the j^{th} subscription plan
 X_j = Total number of readers subscribing to the j^{th} subscription plan
 S_{kj} = Surplus derived to the k^{th} customer segment from the j^{th} subscription plan
 δ_{kj} = 1 if the k^{th} customer segment selects the j^{th} subscription plan and 0 otherwise
 MP = Potential number of readers subscribing to print formats (print market potential)
 MO = Potential number of readers subscribing to digital formats (digital market potential)
 PA, OA = Forecasted print and digital advertising revenues
 PR, OR = Forecasted print and digital readers subscribing to newspaper's plans

Self-selection constraints: Equations (14) through (16) capture self-selection among readers (Moorthy, 1984). In particular, Equation (14) implies that a reader within a segment k will select a plan j only if: (a) the surplus she derives from subscribing to plan j is strictly positive, *and* (b) the surplus she derives from plan j is greater than the surplus she derives from all the other plans offered in the menu. Equation (15) determines the surplus derived by a reader in segment k for the plan j , which is computed as the difference between her reservation price (i.e., WTP) for plan j and the price at which the firm is offering plan j . Next, Equation (16) ensures that readers in segment k pick at most 1 plan from the menu offered by the firm. In sum, these constraints ensure that the platform's choice of an optimal plan takes into account the consumer's individual rationality and incentive compatibility constraints (Moorthy 1984).

Determining market potential: Equations (17) through (19) achieve the objective of deriving the number of potential readers of print and digital formats required for forecasting advertising revenues and the content consumer demand by format corresponding to any alternative menu of subscription plans. First, Equation (17) determines the total demand for a subscription plan j ($\forall j \in J$). Note that Equation (17): (a) allows multiple reader segments to choose the same plan (i.e., δ_{kj} could be 1 for multiple k 's resulting in aggregation of demand from multiple segments

for the same subscription plan j), and (b) recognizes that, within a reader segment, demand for print (N_k^p) and digital (N_k^o) formats are heterogeneous. Therefore, depending on the formats included in the subscription plan j (i.e., depending on λ_j^p and λ_j^o), the equation will determine the appropriate demand from segment k. If a plan includes both print and digital formats (i.e., $\lambda_j^p = 1$ and $\lambda_j^o = 1$), the equation will select the larger of the two populations (i.e., $\max\{N_k^p, N_k^o\}$) as the demand for plan j from segment k.

Equations (18) and (19) determine the total number of potential content consumers in the print and digital formats by aggregating the demand for all plans (X_j) within the menu that include print (λ_j^p) and digital (λ_j^o) formats respectively.

Forecasting advertising and reader demand: the print reader potential (MP) and digital reader potential (MO) are then used in the calibrated market response model (Equations (20) through (23)) to forecast advertiser revenue and content consumer demand within the two formats.

Computing reader profits: Equation (24) is used to compute gross subscription profits from all reader segments. Gross profit from reader segments is simply the product of margin (M_r) and total revenue from the reader segment. Revenue from each segment can be determined by multiplying the demand from the respective segment with the price of subscription plan (P_j) determined by the newspaper firm. However, the projected reader demand (PR, OR) obtained from Equations (20) and (23) represents aggregate demands *by formats*. Therefore, to compute reader revenue, we first retrieve segment-level demand by format by multiplying aggregate demand from Equations (21) and (23) with the proportion of each segment in the firm's existing reader base (φ_k) and price of the subscription plan chosen by the segment (P_j). Note that this will yield the demands of all seven segments for *both* print and digital formats. However, a segment may either subscribe to (a) a pure print plan, (b) a pure digital plan or (c) a plan with both print

and digital formats. Therefore, in the case of (a), the gross profit for segment k is determined as: $(PR_t * P_j * M_{pr} * \varphi_k)$. Similarly, in the case of (b), the gross profit for segment k is determined as $(OR_t * P_j * M_{or} * \varphi_k)$. However, in the case of (c), because the newspaper has never previously offered print + digital bundles, in concurrence with the management, we determine the gross profit for segment k as: $\max\{PR_t, OR_t\} * P_j * M_{pr} * \varphi_k$. Last, the margins for delivering print and digital advertising at the focal newspaper are equal. Therefore, gross profit from advertising is computed as: $(PA + OA) * M_a$.

A Heuristic for Solving the Menu Optimization Problem

The proposed optimization model presents a *discrete combinatorial optimization challenge* for the newspaper. Given K market segments, the newspaper must decide (a) the number of subscription plans to offer in its menu; (b) the composition of subscription plans offered in the menu; and (3) price of each subscription plan such that the chosen menu maximizes its profit from readers as well as advertisers. This is a complex multidimensional nonlinear optimization problem. Consider a simple case where the newspaper is trying to design a subscription plan menu for two segments with 59 distinct plan combinations available to the firm. Ideally, the firm could offer 1 of the 59 plans or 2 of the 59 plans. Therefore, the total number of plans that the newspaper has to evaluate before finding the profit-maximizing menu is $({}^{59}C_1 + {}^{59}C_2 = 1770)$. Additionally, if the newspaper were to test 10 different price points for each plan, the number of combinations to search over before finding the profit-maximizing menu would rise to: $({}^{59}C_1 * 10) + ({}^{59}C_2 * 10 * 10)$, resulting in 171,690 cases. Generalizing this to J plans, K segments and P price points, the total number of combinations needed to be tested before arriving at a solution is: $\sum_{k=1}^K \binom{J}{k} P^k$. As we show in Web Appendix W7, the problem space increases exponentially even with small increases in the number of segments and plan

combinations. Specifically, in the case of our collaborating newspaper where there are 7 segments, the optimizer has to evaluate $3.45706E+15$ menu combinations before finding the solution. A simple software application written in Excel will take more than 5 million minutes to parse these iterations. Therefore, while elaborative ‘brute-force line search’ techniques can guarantee a global solution by sequentially parsing every single combination in the discrete problem space, they can prove to be extremely time intensive and computationally expensive. Therefore, we propose a heuristic to solve the newspaper’s optimization problem within a reasonable amount of time.

The heuristic outlined in Appendix 1 helps the newspaper build the menu by *sequentially assigning a profit-maximizing plan to each segment, subject to plans assigned to prior segments*. Take for instance a case where the newspaper is serving three reader segments, each of which exhibit distinct plan preferences. The algorithm begins with segment 1. Upon evaluating all available plan configurations and ensuring incentive compatibility and individual rationality rules for segment 1, the algorithm assigns a profit-maximizing plan to segment 1. Then, it proceeds to segment 2. The algorithm will again seek a profit-maximizing plan for segment 2 from the available plan alternatives. However, this time, for each plan alternative considered for segment 2, the algorithm evaluates how (a) segment 1 responds to the plan being sought for segment 2, (b) how segment 2 responds to the plan already assigned to segment 1, and (c) how the responses of segment 1 and segment 2 cumulatively affect the firm’s overall profit from readers and advertisers. Both segment 1 and segment 2 may switch plans depending on the surplus they derive from plans made available in the menu in a given iteration; thereby affecting advertising revenue and the firm’s overall profit. After sequentially evaluating all plan alternatives for segment 2, the algorithm will arrive at a menu for Segment 1 and Segment 2 such

that the plans together (or possibly just one plan) deliver the highest total profits to the firm while meeting incentive compatibility and individual rationality constraints for the segments. Subsequently, the algorithm proceeds to segment 3 and repeats the process. By the time the algorithm has evaluated the last plan alternative for segment 3, it would have identified a combination of plans that will generate maximum profit for the firm among all the available combinations. Note that each plan within the menu can be preferred by more than one segment. Therefore, the total number of plans available in the final menu (or a menu in any iteration for that matter) may be less than or equal to the total available segments.

Benefits of the proposed heuristic over a line search approach: From a computational cost viewpoint, the proposed heuristic provides two key benefits over a brute force algorithm: it (a) evaluates fewer plan combinations, and (b) evaluates fewer price points. In particular, the algorithm outlined in Appendix 1 requires each plan (J) to be evaluated only once for every segment (K) and each prior segment be checked for a potential plan switch, resulting in a total of only $(K \times J \times \sum_{k=1}^K (k - 1))$ evaluations, which takes a simple software application written in Excel less than 30 seconds to execute on a Pentium 4 processor. Similarly, by using segments' WTP to set the price for an assigned plan (as opposed to using pre-determined price points), the heuristic will substantially reduce the computational burden. Specifically, the heuristic circumvents the need to assign upper and lower bounds for each plan. Setting a large upper bound could result in wasteful iterations because segments' WTP may not be as high as the price points evaluated by the algorithm. On the other hand, setting a small upper bound may result in suboptimal prices because segments' WTP may be higher than the upper bound of the price points.

A potential caveat of this heuristic is that multiple equilibria can exist with different segment orders (i.e., the order in which segments are processed by the algorithm). This is because the plan assigned to segment k is not only contingent on segment k 's economic surplus for the assigned plan but also depends on all the plans assigned to segments *prior* to segment k . Therefore, global optimality using the proposed heuristic is not guaranteed. This, however, is a common problem in the extant product line literature that uses heuristic techniques (Belloni et al. 2008; Luo 2011). We partly mitigate this problem by running our algorithm numerous times with various segment orders. Additionally, in order to check whether or not the line search technique and our proposed heuristic produce the same results, we reduced the dimensionality of the problem by restricting the number of segments to two⁴ and then ran both the algorithms. The results confirmed that both techniques produce the same results.

Profit Maximizing Solutions under Different Business Models

Initial values for the optimizer: We use the 59x7 WTP matrix obtained from step 1 and the parameter estimates of the calibrated market response model obtained in step 2 to derive a profit-maximizing menu of subscription plans. A complete list of input values for the optimizer are provided in Web Appendix W8. Note that all WTP estimates were rounded to the nearest \$0.25 to mimic newspaper subscription pricing in the real world. We obtained margin information from the collaborating firm. Currently⁵, the newspaper is making a margin of about 0.547 on ad revenue (M_a) and 0.077 on print subscription revenue. Because the newspaper was not

⁴ We could have picked a higher number of segments but the amount of time it took the line search algorithm to go over all the possible scenarios and find a profit maximizing plan was abnormally high. So, we restrict our robustness check to a two-segment case. We repeated the process for multiple two segment-pairs to rule out any segment selection bias.

⁵ Current period is the period following the last period in the archival dataset. We do not reveal the exact years of data collection for confidentiality purposes (we are bound by NDA with the newspaper).

monetizing its digital content, we surveyed several newspaper practitioners to obtain a benchmark margin on digital subscription revenue of 0.20.

Establishing the baseline: current newspaper performance: We will describe the status quo with respect to subscription plans and gross profits at the collaborating newspaper. This information will serve as the baseline for assessing the effectiveness of menus derived under proposed model and other business model and format strategies. The newspaper is currently offering two paid-subscription plans to its readers: 7-day print at \$5.00/week and Sunday only print at \$2.75/week. The current set of reader offerings is identical to a *pure component strategy* because all plans (i.e., 7-day, Sunday and Digital) are offered separately to the readers. As reported by the newspaper, the firm made \$3,393,886 through print subscriptions, \$7,252,415 through print advertising and \$706,142 through digital advertising in the current period. Using margins described in the previous section, the newspaper's gross profit in the current period is: $(0.077 * \$3,393,886) + 0.545 * (\$7,252,415 + \$706,142) = \$4,599,082$. This gross profit marks the baseline for all further analyses. We will evaluate outcomes from various newspaper strategies with respect to total gross profits (\$4,599,082), gross profits from subscription ($0.077 * \$3,393,886 = \$261,669$) and gross profits from advertising ($0.545 * (\$7,252,415 + \$706,142) = \$4,337,414$) in the current period.

Now, we briefly describe optimal menus along with their profits under each of 4 common business model and organizational management scenarios prevailing in the United States.

Siloed business model strategy: Historically, newspaper circulation and advertising departments have focused on their own objectives in budgeting and resource allocation decisions (Willis and Willis 1988), i.e., adhered to a 'Siloed' business model. Such decision-making by circulation departments is still pervasive in the U.S. (Newspaper Association of America 2012). To capture

this situation, we modified the objective function of the proposed general optimization model M1 to maximize gross profits from subscriptions alone: Maximize $\sum_j B_j(PF_j)$. Consequently, our heuristic determined a menu of subscription plans that *maximized gross profit from subscriptions without accounting for the consequences for advertising revenues*. Then, the heuristic computed and added the gross profits from advertisers using the reader demand generated by the subscription profit-focused subscription menu. Table 4 summarizes the results.

<< Insert Table 4 about here >>

Three interesting results emerge from the analysis of the siloed business model:

- (a) First, the subscription profit-maximizing menu is a “*partial mixed bundle*” of print and digital formats (i.e., 7-day + digital, Sunday + digital, and digital-only plans).
- (b) Second, gross profits from subscriptions in the Siloed model are higher (\$744,935) than those in the current scenario (\$261,668). This result is contrary to the traditional notion that charging for digital content will lead to a decline in subscription revenues.
- (c) Third, gross profit (\$3,207,713) from advertising in the Siloed model is lower than that in the current scenario (\$4,337,413). This is interesting because it shows that the newspaper will generate more gross profits from advertising by operating under a Siloed business model and charging only for print content (i.e., current situation) than it would by operating under a Siloed business model and charging for both print and digital content.

Integrated business model strategy: In contrast to a siloed model, an integrated business model entails both circulation and advertising departments working together. Specifically, managers overseeing both departments devise subscription plans together to maximize the sum of gross profits derived from subscriptions as well as advertising. While practitioners speculate that designing multi-format subscription plans by taking consumers’ and advertisers’ preferences into account could yield more profitable outcomes (Newspaper Association of America 2012), there has been no empirical evidence, to the best of our knowledge, supporting this claim. Therefore, to test this claim, we obtained a profit-maximizing menu using the objective function specified in

Equation (13) and the algorithm outlined in Appendix 1. Three interesting observations can be made from the output obtained under integrated business model strategy (see Table 4):

- (a) First, the profit-maximizing menu is a “*pure bundle*” of print and digital formats (i.e., 7 day + digital and Sunday + digital plans).
- (b) Second, while gross profit from subscription in the integrated model (\$606,709) is *higher* than that in the baseline scenario (\$261,669), it is *lower* than that in the siloed model scenario (\$744,935). This is interesting because: (1) it reaffirms that charging for digital content can increase subscription profit, and (2) it shows that offering a “*pure bundle*” results in lower subscription profit than offering a “*partial mixed bundle*”.
- (c) Third, gross profit from advertising in the integrated model (\$4,785,254) is higher than that in the baseline scenario (\$4,337,413) as well as in the siloed model (\$3,207,713.). This is also interesting because: (1) it demonstrates that charging for digital content can increase profit from advertising, and (2) it shows that “*pure bundle*” offering results in higher advertising profits than pure component or partial mixed bundling strategies.

Reduced print frequency format strategy: A decline in print circulation and advertising revenues in the past decade has forced newspapers to consider the option of cutting back on their print frequency as a means to stabilize their finances and restore profitability. While there are numerous debates on this topic in the popular press, there is very little scientific evidence demonstrating the financial viability of the reduced print frequency strategy. Therefore, to glean insight into the effectiveness of ‘reduced print frequency format strategy’ in the context of the newspaper studied here, we restricted the plan alternatives to Sunday + digital bundles and pure digital plans (i.e., we eliminated bundles that included 7 day print from the plan alternatives) and subsequently, derived profit-maximizing plans within the integrated business model framework.

As shown in Table 4, the profit-maximizing menu under this strategy comprises two Sunday + digital bundles. While the total gross profit obtained under the reduced print frequency strategy (\$5,214,766) is 3.4% lower than that obtained when the firm operates without any reductions in print frequency (\$5,391,964), the total gross profit is still 13.39% higher than that in the current scenario where the firm is operating under the print-only strategy (\$4,599,082).

Therefore, this analysis confirms the financial viability of the reduced print frequency strategy in the short-term.

Digital-only format strategy: Another strategy pondered by some newspapers to stabilize their financial situation is the complete elimination of the print publication. We refer to this as the ‘digital-only format strategy’. A small number of newspapers such as *The Ann Arbor News* have implemented the digital-only strategy in recent times. To determine the implications of adopting a digital-only strategy within the context of the collaborating firm, we restricted plan alternatives in the optimization model to pure digital plans (i.e., we eliminated bundles that contained 7-day and Sunday print options from the plan alternatives) and subsequently, ran our optimizer.

The results in Table 4 demonstrate that the profit-maximizing menu under this strategy comprises three variants of the digital plans. While the gross profit from circulation in the digital-only strategy (\$397,527) is higher than that in the baseline scenario (\$261,668.), gross profit from advertising (\$445,468) and overall gross profit (\$843,041) in the digital-only strategy are substantially lower than that in the baseline scenario. In summary, this analysis suggests that our collaborating newspaper will face substantial profit declines in the short-term under the digital-only scenario.

Accounting for Variance in Content Consumers’ WTP

Thus far, we have evaluated profit-maximizing menus under various business models and format strategies assuming *average* segment-level WTP estimates. These mean estimates are point estimates that do not capture the variability of WTP among the respondents. A manager could be interested in knowing how variance impacts the menu composition and profits because variance determines the risk involved in offering a plan at its mean price. Take for instance a plan j with high variance. A manager would be less certain about offering plan j at its mean price

because she would have less confidence in the number of readers within a segment who will derive positive surplus from subscribing to plan j at that price. On the other hand, a manager would be more certain about offering a plan m at its mean price if plan m exhibits smaller variance in WTP because the probability of readers who would derive positive surplus from subscribing to plan m at mean WTP would be higher.

Therefore, to account for managers' risk preferences with respect to variance in segment-level WTP estimates, we added the following constraint to the proposed optimization model:

$\sigma_{jk}^2 \leq \tilde{\sigma}^2$ where, σ_j^2 is the variance in the WTP of plan j within segment k and $\tilde{\sigma}^2$ is the risk tolerance of the manager. We simulated the algorithm for various values of $\tilde{\sigma}^2$ and obtained profit-maximizing menu parameters. Several interesting results emerged from this analysis (see Web Appendix W9 for details):

- (a) First, profit-maximizing menus for all risk levels were “*pure bundles*” comprising of 7 day + digital and Sunday + digital plans, which is consistent with the result using point estimates.
- (b) Second, gross profit increased with an increase in $\tilde{\sigma}^2$. This finding is consistent with the notion that high risk yields high reward. Additionally, total gross profits at all risk levels are still higher than those in any other alternative business model.
- (c) Third, gross profit from advertising remained constant for all risk levels. This finding demonstrates that there exists a portfolio of print + digital bundles from which the manager can choose from depending on her risk level, without affecting the demand from readers and gross profit from advertising.
- (d) Fourth, price dispersion (computed as maximum price – minimum price) among plans within the menu decreased as the risk decreased. This indicates that a manager will price the plans more similarly as she becomes more risk-averse.

In summary, while profits varied in magnitude, substantial findings with respect to menu composition and profitability under an integrated strategy remained unaltered even after accounting for variance in WTPs. This robustness check helped us obtain buy-in from the management (see Web Appendix W10 for managers' responses), which was crucial to ensure

continued adoption of the decision tool (van Bruggen and Wierenga 2010). Additionally, to enhance the firm's adoption of this tool for future decision making, we coded the heuristic using Visual Basic language and implemented the decision framework in Microsoft Excel application.

Conclusion

Media platforms such as newspapers have been facing a steady decline in revenues from traditional formats such as print, radio and television for over a decade (Pew Research Center 2014). At the same time, traditional formats are still the dominant revenue sources at these firms. Further, proliferation of formats and versions is presenting media platforms with unprecedented opportunities as well as challenges with respect to packaging their media content. Consequently, media platforms are confronted with the problem of designing their offerings such that they can sustain revenue growth from contemporary digital offerings while continuing to maintain revenues from their legacy formats (e.g., print, radio and television). To that end, they need a decision tool that can provide them with intelligence on designing profit maximizing offerings.

Our research addresses this topical menu-design problem confronting the modern-day media platforms. Specifically, leveraging individual format and version preference data from content consumers and the firm's aggregate transaction data, the study builds a novel mixed integer nonlinear programming algorithm that can effectively determine the optimal menu of subscription plans for readers. Specifically, the study demonstrates an approach to integrate a-priori segment-level reader preferences for multi-format multi-version subscription plans and a calibrated market response model that can forecast reader and advertising demand into an implementable coordinate gradient ascent search based heuristic to determine profit-maximizing menus under various business model and format strategies.

Contributions to Marketing Theory and Practice

From a theoretical standpoint, this study augments literatures on pricing in two-sided markets, format bundling, format-versioning and product line design in multiple ways. While the majority of research in marketing and economics has addressed various aspects of the firm's product offering and pricing problem in a one-sided market, a holistic solution that addresses the contemporary media platform's menu-design problem has not yet been offered. More generally, a product line design and pricing problem that incorporates CMNEs and installed-base effects for multi-format multi-version media content has not been addressed before in the literature. The three-step approach proposed in the present research offers clear directions for negotiating the conceptual and practical challenges and solving this type of problem. In the process, we also extend Moorthy's self-selection theory to two-sided markets. Moreover, this study adds to a very nascent literature that examines *asymmetric* CMNEs (Gomes and Pavan 2013; Veiga and Weyl 2010) by proposing and calibrating a *multi-format* market response model for a media platform firm that allows for such CMNEs. From a methodological standpoint, the proposed approach offers a novel and implementable means by which newspapers can integrate their *aggregate-level* market data with *disaggregate-level* reader data and a novel heuristic for solving the complex optimization problem efficiently and rapidly. From a managerial viewpoint, to the best of our knowledge, this research is the first to evaluate profitability of various newspaper business models and format strategies for stabilizing newspaper finances debated in the popular press, using actual market data-based models. The insights from our proposed optimizer are thereby valuable for not just newspaper firms but also for other ad-supported media platform industries.

Limitations and Directions for Future Research

As with any study, this research is also not without limitations. However, these limitations offer numerous opportunities for future research. First, while our proposed decision-

framework is generalizable to all ad-supported media platforms, the analysis was customized to incorporate subtleties of the newspaper business. Therefore, future research can extend the proposed framework by incorporating unique features of other media platforms. For instance, Hulu provides its content consumers with an option to select the type of ads, number of ads and length of ads. Similarly, television broadcasting stations such as ESPN are now experimenting with dynamic metering strategies where in different content categories (e.g., baseball, hockey, soccer etc.) there are different free-access limits (i.e., meters) (e.g., Lambrecht and Misra 2015). Moreover, leveraging the fact that multi-format touchpoints could enhance ad recall and effectiveness, many media platforms such as television broadcasting stations are starting to offer a menu of plans to advertisers. Likewise, media platforms may start offering personalized plans to content consumers based on “cookie” data, while others may allow their content consumers to build their own personalized bundles. Consequently, we urge future research to explore how these unique characteristics affect menu configurations.

Similarly, future research can also incorporate more up and coming advertising trends into the proposed menu design framework⁶. For instance, programmatic advertising is eliminating the need for human interaction in the digital ad buying process. A recent article in Ad Age notes that programmatic advertising will soon make up \$14.88 billion of the approximately \$58.6 billion digital advertising market (Kantrivitz 2015). This trend could result in platforms shifting their marketing investments from *outside* sales forces to *inside* sales forces and information technology in order to deliver seamless digital ad-buying experience to their advertising customers. Similarly, with the rise of “geo-targeting” and “geo-conquesting”, advertisers are now demanding more precise target audiences. This could significantly affect

⁶ We thank an anonymous reviewer for suggesting this future research direction.

how pure-digital platforms such as Hulu can use the proposed framework. For instance, the aggregate reader demand variable in the advertising response models would have to be replaced with spatial, demographic and location information. More along the lines of mobile advertising, industry experts also predict an increase in the use of “beacon proximity signals” for geo-targeting (Moore 2015). If so, this will result in significant changes in marketing-mix and IT expenditures at media platforms. Moreover, there are numerous other developments on the horizon in the digital ad delivery space. For instance, just as webpages are adaptable to mobile devices, Google’s new responsive ‘AdSense’ program adjusts the ads to different screen sizes. Similarly, ‘Snap Banners,’ which was first invented by *People* magazine, provides a more fluid and interactive experience to mobile users. Digital content delivery platforms are incorporating such developments into their product design. Consequently, these developments could present media platforms with new ways to monetize their content. For example, platforms can offer a base version of the app and a more ‘native’ mobile app that presents an enhanced viewing experience for an additional price. Future research can incorporate such developments into our proposed menu design framework.

Next, this research presents a single-period static optimization framework that does not incorporate learning among content consumers and advertisers in future periods. One would need observed data to empirically examine multi-stage dynamic decisions. Moreover, while readers may frequently switch plans, newspaper firms do not change their *menu* of offerings frequently. This is because a change in offerings would require newspapers to make necessary changes in other marketing mix instruments such as advertising, promotion and distributions, which is very expensive. Hence, managers at our collaborating newspaper were willing to accept a static solution. However, as more newspapers update their menus with multi-format multi-version

subscription plans, scholars, in the future, should be able leverage our framework to propose dynamic multi-period optimization frameworks. Similarly, while our framework uses profit as the performance metric, it can be easily adapted to long-term performance metrics such as customer equity, retention and acquisition. Future research can propose such model extensions and validate whether or not the proposed menu solutions under various business models change with performance metrics.

Last, another worthwhile future research direction is to incorporate marketing-mix changes at the time of multi-format menu introductions into the proposed menu design framework. As the number of ad-supported media platforms that offer multi-format subscription plans increase, data on reader and advertiser responses to market-mix changes during multi-format menu introductions will become available. Consequently, researchers can incorporate this information into the market response model and study the effect of such intermittent marketing-mix changes during new subscription menu deployments on optimal plan compositions.

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Table 1: A Three Step Approach for Deriving a Profit Maximizing Menu of Multi-format Subscription Plans

Step	Theoretical underpinnings	Method	Key outcomes
(1) Measuring content consumers' WTP for various possible multi-format subscription plans	Individual utility maximization theory (McFadden 1986)	Hierarchical Bayes Choice-based Conjoint analysis of individual choice data	* Individual part-worth data for various formats, versions and price * Willingness to pay for all possible multi-format plan combinations * Assessing content consumers' market potential
(2) Calibrating two-sided market-level response model including content consumer and advertiser 'demands' by format	Theory of two-sided markets (Rochet and Tirole 2006)	Market response modeling of archival data	* Calibrated market response model for content consumers and advertisers and by various formats
(3) Determining profit maximizing menu of multi-format subscription plans using outcomes of steps 1 and 2	Theory of self-selection with incentive compatibility and individual rationality (Moorthy 1984)	Mixed integer nonlinear program (MINLP)	* A heuristic to solve a complex discrete combinatorial optimization problem * Profit maximizing menus under various business models and format strategies.

Table 2: Average Part-Worths of Design Attributes and Interactions by Reader Segment and Survey Version

	Segment 1		Segment 2		Segment 3		Segment 4		Segment 5		Segment 6		Segment 7	
	v1	v2	v1	v2	v1	v2	v1	v2	v1	v2	v1	v2	v1	v2
Print format														
7 day print access	-1.41	-3.29	1.00	1.71	-1.72	-1.65	-0.16	-4.41	2.25	2.75	-2.16	-6.10	4.23	5.73
Sunday only print access	-0.44	0.46	0.16	0.08	-0.08	-0.37	0.52	2.44	-1.49	-0.97	0.65	1.46	-2.05	-1.24
No print access	1.85	2.83	-1.16	-1.79	1.79	2.03	-0.36	1.97	-0.77	-1.78	1.52	4.64	-2.18	-4.49
Online format														
Unlimited online access optimized for each device	3.39	3.64	1.83	3.91	2.40	2.58	2.65	3.68	2.79	2.87	3.50	2.56	0.76	1.94
Access limited to 20 stories per week optimized for each device	-0.75	-0.05	-0.14	0.48	-0.68	-0.55	-0.38	-0.07	-0.47	0.55	-1.06	-0.72	-0.97	0.16
Unlimited access on smartphone only	-1.98	-1.02	-0.74	-0.53	-0.43	0.15	-0.88	-0.72	-1.52	-1.28	-2.66	1.05	-1.77	-0.91
Access limited to 20 stories per week on smartphone only	-2.04	-3.17	-1.11	-1.29	-0.04	-1.42	-1.77	-1.35	-1.23	-2.30	-4.66	-2.83	-0.50	-1.50
No online access	1.37	0.60	0.15	-2.57	-1.25	-0.77	0.39	-1.54	0.44	0.16	4.87	-0.06	2.48	0.30
Smartphone app format														
Unlimited app access with ads	-1.70	-1.53	-0.77	1.27	0.13	0.00	-1.84	-0.71	-1.32	-1.17	-0.92	-1.35	-2.13	0.05
No app access	1.70	1.53	0.77	-1.27	-0.13	0.00	1.84	0.71	1.32	1.17	0.92	1.35	2.13	-0.05
Tablet app format														
Unlimited app access with ads	-1.80	-0.19	-0.74	0.80	1.92	1.49	-0.51	0.62	-0.49	-0.08	-2.97	0.51	-1.40	-1.02
No app access	1.80	0.19	0.74	-0.80	-1.92	-1.49	0.51	-0.62	0.49	0.08	2.97	-0.51	1.40	1.02
Format interactions														
Print format x online format	0.41	0.51	0.14	0.30	0.78	0.93	0.43	0.20	0.88	0.34	0.48	0.72	0.83	0.22
Print format x smartphone app format	-1.26	0.03	-0.09	-0.14	-0.50	-0.21	0.06	-0.51	0.15	0.11	-1.73	-0.29	0.99	0.62
Print format x tablet app format	0.90	-0.06	1.06	0.75	0.68	0.41	0.62	0.03	0.71	0.40	1.92	1.44	0.54	0.14
Online format x smartphone app format	2.98	1.44	1.56	-0.67	1.10	0.37	2.02	1.03	1.61	0.81	3.94	2.44	1.99	-1.09
Online format x tablet app format	1.84	0.34	0.45	-0.43	-0.96	-0.35	0.63	-0.87	0.22	-0.05	3.91	-1.26	0.45	1.66
Smartphone app format x tablet app format	0.04	1.21	-0.37	-0.57	-0.38	0.70	0.37	1.04	0.41	1.10	-2.57	0.10	0.40	0.43
None (no choice option)	10.13	9.85	5.25	7.55	8.83	8.48	7.58	10.23	5.61	5.67	13.40	9.98	3.60	4.07

Table 3: Model Comparison and Key Parameter Estimates in the Market Response Model

	Model parameters					Forecast accuracy		Model fit statistics	
	Trend, seasonality, cyclicity & recession	Marketing investments	Cross market network effects	Carryover / installed base effects	Accounting for unobservable effects	MAPE (across equations)	MAD (across equations)	BIC	Durbin Watson statistic
Model 1	✓					2.828%	0.403	-1006.218	0.287
Model 2	✓	✓				2.763%	0.395	-1513.297	0.718
Model 3	✓	✓	✓			2.838%	0.406	-1489.757	0.709
Model 4	✓	✓	✓	✓		1.638%	0.239	-1710.718	1.456
Model 5	✓	✓	✓	✓	✓	1.560%	0.228	-1755.812	2.252

Note: First 77 observations and last 30 observations were used as estimation and holdout samples for assessing forecast accuracy.

Print format elasticity estimates		Digital format elasticity estimates	
CMNE of readership on advertising \$\$	0.413***	CMNE of readership on advertising \$\$	0.327***
CMNE of advertising \$\$ on readership	0.028***	CMNE of advertising \$\$ on readership	0.031***
Effect of quality investments on readership	0.047***	Effect of quality investments on readership	0.112***
Effect of distribution investments on readership	0.031**		
Effect of sales force investments on advertising \$\$	0.194***	Effect of sales force investments on advertising \$\$	0.350***
Effect of print market potential on advertising \$\$	1.843***	Effect of digital market potential on advertising \$\$	0.288 (ns)
Effect of print market potential on readership	0.181***	Effect of digital market potential on readership	0.524***
Carryover/installed based effect of previous period advertising \$\$	0.293***	Carryover/installed based effect of previous period advertising \$\$	0.761***
Carryover/installed based effect of previous period readership	0.272***	Carryover/installed based effect of previous period readership	0.235***

***p < 0.01, **p < 0.05, ns – not significant, CMNE – cross market network effect

Table 4: Profit Maximizing Menus under Various Business Model and Format Strategies

	Siloed Business Model	Integrated Business Model	Reduced Print Frequency Format Strategy	Digital Only Format Strategy
Menu composition	7 day + all digital at \$5.25/week	7 day + all digital at \$6.25/week	Sunday + all digital at \$2.25/week	All digital at \$2.00/week
	Sunday + all digital at \$3.00/week	Sunday + all digital at \$2.25/week	Sunday + unlimited online access + unlimited tablet app access at \$2.00/week	Unlimited online access + unlimited smartphone app access at \$1.50/week
	Sunday + unlimited online access + unlimited tablet app access at \$2.25/week	Sunday + unlimited online access + unlimited tablet app access at \$2.00/week		Unlimited online access at \$1.00/week
	All digital at \$2.25/week			
Gross profits from print advertising	\$2,699,808	\$4,267,835	\$4,267,835	\$0.00
Gross profits from digital advertising	\$507,905	\$517,420	\$517,420	\$445,469
Gross profits from print bundles	\$534,450	\$606,709	\$429,512	\$0.00
Gross profits from digital only circulation	\$210,486	\$0.00	\$0.00	\$397,572
Total gross profits from advertising	\$3,207,713	\$4,785,255	\$4,785,255	\$445,469
Total gross profits from circulation	\$744,936	\$606,709	\$429,512	\$397,572
% increase in gross profits from baseline scenario	-14%	17%	13%	-82%

Figure 1: Predictive Accuracy of the Calibrated Market Response Model

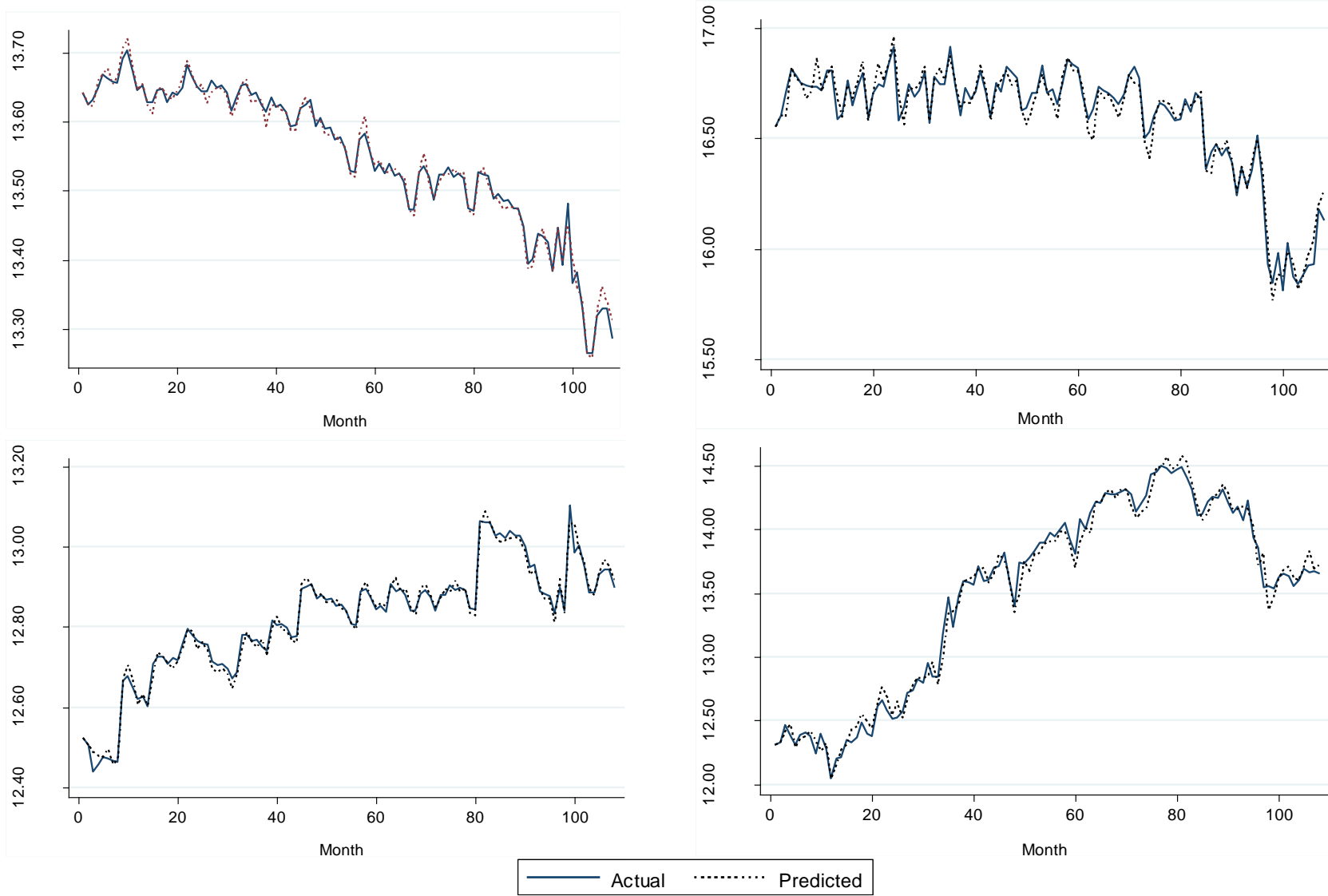
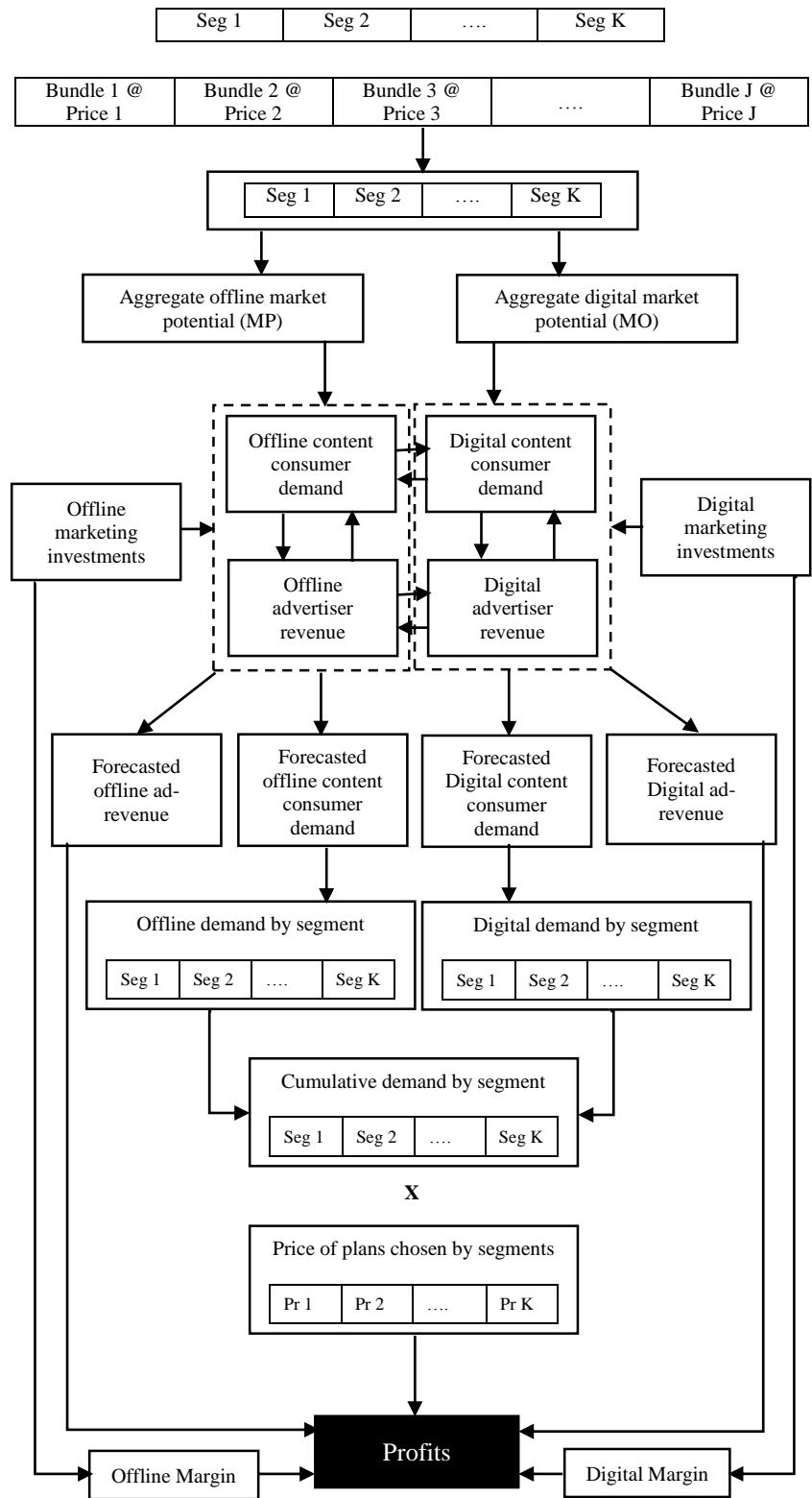


Figure 2: A Framework to Design Subscription Menu for Ad Supported Media Platforms



Target market comprises of multiple segments

The platform offers a menu of multi-format subscription plans

Each segment will pick a plan that offers the greatest positive utility among all plans available in the menu (eq. 14 – 17)

Based on segment’s plan preferences, the platform can determine market potential within each format (eq. 18 – 19)

The platform can then use a market response model to forecast content consumer demand and advertiser revenue in offline and digital formats (eq. 20 – 23)

To determine content consumer *revenue*, the platform would need to first determine segment-level content consumer demand. Therefore, the platform can split the forecast based on the proportion of each segment (k) in the target population (φ_k)

The platform can aggregate content consumer demand by segment using eq. 24

The platform can obtain revenue from content consumers by multiplying each segment’s demand with the price of the plan that the segment picked in the third step above.

In the last step, the platform will determine the total profits using eq. 13

Appendix 1: Algorithmic Representation of the Proposed Optimizer

Outer Loop: For each segment k and for each plan configuration j , repeat the following:

Inner Loop:

Module 1: **Step 1 (Incentive Compatibility Step):** Pick a price \tilde{p}_j for plan j such that:

- i. $\tilde{p}_j = RP_{kj}$ if plan j has not been assigned to any other segment prior to segment k , the best possible price for \tilde{p}_j is RP_{kj}
- ii. $\tilde{p}_j = \min (RP_{kj}, RP_{mj})$ if plan j has been assigned to another segment m prior to k , the best possible price for \tilde{p}_j is $\min (RP_{kj}, RP_{mj})$

Step 2 (Individual Rationality Step): Verify plan switches among segments. Specifically, check for two scenarios:

- i. $(RP_{mj} - P_j) > (RP_{mq} - P_q)$ for $j \neq q, \forall m$. A segment (say, segment m) that is assigned another plan (say, plan q) prior to segment k may switch to plan j if the surplus derived by segment m from subscribing to plan j is greater than that from subscribing to plan q .
- ii. $(RP_{kj} - P_j) < (RP_{kq} - P_q)$ for $j \neq q, \forall q$. Segment k may switch to another plan (say, plan q) already assigned to a segment (say, segment m) prior to itself, if the surplus derived by segment k from subscribing to plan j is less than that from subscribing to a plan already available in the menu.

Module 2: **Step 3 (Market Potential Computation Step):** Follow Equations (18)-(19) to compute potential number of print and digital readers

Step 4 (Demand Forecasting Step): Follow Equations (20)-(23) to forecast reader demand and advertising revenues

Step 5 (Profit Computation Step): Taking into account plan assignments and segment switches, compute profit $\tilde{\pi}_j^k$ (defined as cumulative profits from all segments up to segment k after adding plan j to the menu)

Step 6 (Profit Evaluation Step): If $\tilde{\pi}_j^k > \tilde{\pi}_q^k, \forall q < j$ (i.e., profits when plan j is assigned to segment k are greater than profits when plan q is assigned to segment k) or $\tilde{\pi}_j^k > \tilde{\pi}^{k-1}$ (i.e., profits when plan j is assigned to segment k are greater than profits when segment k is not assigned any plans), add plan j to the menu, proceed to Step 1 and repeat the process for the $(j+1)^{th}$ plan.

Step 7 (Profit Evaluation Step): If either condition in Step 6 fails, drop plan j from the menu, proceed to Step 1 and repeat the process for the $(j+1)^{th}$ plan.

Web Appendix W1: An Algorithm to Compute Willingness to Pay

An algorithm was developed in Excel using Visual Basic to automate the computation of the willingness to pay for all possible plan configurations. A total of 59 plan configurations (denoted by J) are possible using the 4 design formats (i.e., (3 print alternatives * 5 online alternatives * 2 smartphone app alternatives * 2 tablet app alternatives) – 1 alternative where neither print nor online nor smartphone app nor tablet app are offered). The algorithm can be outlined as follows:

- Step 1:** $\forall i \in I$ and $\forall j \in J$, compute $u_{ij|-p} = \mathbf{x}'_j \beta_{ix}$, where \mathbf{x}'_j is a 1×12 matrix of design attribute levels with each row in the matrix assuming a 1 or a 0, which reflects the presence or absence of an attribute level in plan configuration j.
- Step 2:** $\forall k \in \{1, 2, 3, 4, 5\}$, compute $U_i(\mathbf{x}_j, p_k) = (u_{ij|-p} + p_k \beta_{ip})$ where p_k is the k^{th} price level used in the conjoint study. p_1 through p_5 are in ascending order and $U_i(\mathbf{x}_j, p_k)$ is the utility of reader i for the j^{th} plan configuration and k^{th} price level.
- Step 3:** Select upper bound, $Ub_{ij} = U_i(\mathbf{x}_j, p_k)$ s.t. $U_i(\mathbf{x}_j, p_k) \geq \alpha_i$ for the highest possible p_k . If $U_i(\mathbf{x}_j, p_1) < \alpha_i$ set willingness to pay p of reader i for plan configuration j equal to 0, skip steps 4 and 5 and proceed to the next plan.
- Step 4:** Set lower bound, $Lb_{ij} = U_i(\mathbf{x}_j, p_{k+1})$. If $k + 1 > 5$, set $Lb_{ij} = Ub_{ij}$
- Step 5:** Compute $\Delta U_{ij} = \{U_i(\mathbf{x}_j, p_k) - \alpha_i\}$ and use ΔU_{ij} to linearly interpolate between price levels in Ub_{ij} and Lb_{ij} to find a price p s.t., $U_i(\mathbf{x}_j, p) = \alpha_i$. p is the willingness to pay of reader i for plan configuration j.

Web Appendix W2: Demographic Profile of the Survey Sample

	Survey Version 1	Survey Version 2
Sample Size	523	621
Gender		
Male	301	343
Female	221	272
Other	1	6
Age		
18-24	6	8
25-34	38	55
35-44	71	64
45-54	112	135
55-64	172	199
65+	124	160
Race		
Hispanic/Latino	7	7
Asian, Pacific Islander	21	16
White, Caucasian	428	532
Black, African American	6	8
American Indian, Eskimo or Alaskan Native	4	9
2 or more races	22	16
Another race	8	4
Refused	27	29
Income		
Under \$25,000	14	32
\$25,000 - \$34,999	17	32
\$35,000 - \$49,999	40	49
\$50,000 - \$74,999	86	84
\$75,000 - \$99,999	73	96
\$100,000 - \$149,999	115	118
\$150,000 or more	94	107
Refused	84	103
Education		
Grade school	0	0
Attended high school but did not graduate	2	0
Graduated high school	13	22
Trade school	4	4
Some college	94	136
Completed 4-year degree	156	171
Some post-grad work	69	83
Completed post-grad degree	185	205

Web Appendix W3: A-Priori Segmentation Questions and Description of the Segments

How strongly do you agree or disagree with each of the following statements using a scale of 7 to 1 where 7 means you strongly agree and 1 means you strongly disagree and using any number in between.

- a. Online news is better since it can be updated quicker
- b. I like to be among the first to learn about new technology
- c. I usually don't try new technology until after it becomes main stream
- d. I like to get my news from multiple sources so I can do my own research and draw my own conclusions
- e. Advertising and shopping information helps me learn about new products
- f. Advertising and shopping information helps me find out about what's on sale
- g. People can get all the information they need just by accessing the Internet
- h. The printed newspaper is outdated and no longer serves my needs
- i. Printed newspapers are a good value for the money
- j. I won't pay for news, because I can get it for free
- k. I like reading from a printed newspaper versus online
- l. Sunday wouldn't be Sunday without the printed newspaper

=====

On a scale of 1 to 7, how often do you use each of the following sources to learn about LOCAL news and information?

- a. Social media sites such as Twitter, Facebook, LinkedIn and Instagram
- b. Local TV stations
- c. Printed daily or Sunday newspapers
- d. Local newspaper websites
- e. News apps on a tablet device
- f. News apps on a smartphone
- g. Search engines or news portals such as Google, Yahoo or Bing
- h. Local NPR station

- 1 - Several times a day*
- 2 - At least once a day*
- 3 - 2 to 3 times a week*
- 4 - At least once a week*
- 5 - 2 to 3 times a month*
- 6 - Once a month or less*
- 7- Never*

Description of the Segments

The seven strategic segments can be described as follows. The first segment comprises the “career-focused urbanites.” Readers in this segment are relatively younger, largely male and live in the metro-area. They are technologically advanced, possess advanced degrees and earn higher income. Readers in this segment typically do not read the print version of the newspaper and expect free news. The second segment includes the “young traditionals”. As the name suggests, readers in this group are also relatively younger and largely female. They are technologically savvy, seek news from multiple news sources and favor the Sunday version of the print newspaper and the digital access to the newspaper’s website. The third segment comprises the “connected news-techies.” This group of readers is technologically savvy, addicted to mobile and tablet devices and the social media, and relies on the internet for news and information. Consequently, this segment values the digital access to the newspaper’s website more than the print versions. Next, the fourth segment includes the “suburban social shoppers.” They define themselves as family-oriented, traditional and thrifty. They actively seek coupons and are driven by soft-news in the newspaper (e.g., shopping/sales information and consumer-driven content). They favor Sunday print version over the 7 day print and digital access. The fifth segment comprise the “progressive urbanites.” These readers are slightly older, earn higher income, are environmentally conscious and interested in community issues. More than any other segment, they consider themselves “news junkies” and seek out news updates constantly. While they prefer print version over online version, they are willing to pay for a print and digital access bundle to get breaking news alerts and constant news updates. The sixth segment comprises the “family-focused socials”. This younger, predominantly female segment is focused on family and uses technology to connect and reach out. They are heavy users of social media and are eager to

learn about places to go and things to do. Moreover, they are less interested in hard news. The last segment includes the “baby-boom loyalists”. As the name indicates, they are older, loyal readers with mainstream values. They have the strongest print affinity. Readers in this segment agree strongly that Sunday wouldn’t be Sunday without the newspaper and that print newspapers are a good value for the money. They are digitally connected, but their internet and mobile usage lag behind the rest of the market segments.

Segment Composition within the Survey Sample

Segment Number	Segment Definition	Version 1 n (%)	Version 2 n (%)	Both versions n (%)
1	Career focused urbanites	110 (21.00%)	154 (24.80%)	264 (23.08%)
2	Young traditionals	81 (15.50%)	96 (15.50 %)	177 (15.47%)
3	Connected news techies	84 (16.10%)	83 (13.40 %)	167 (14.60%)
4	Suburban social shoppers	48 (09.20%)	59 (05.60 %)	107 (09.35%)
5	Progressive urbanites	117 (22.40%)	107 (17.20 %)	224 (19.58%)
6	Family-focused socials	34 (06.50 %)	43 (06.90%)	77 (06.73%)
7	Baby boom loyalists	49 (09.40%)	79 (12.70%)	128 (11.19%)

Web Appendix W4: Summary of Challenges and Robustness Checks Performed during Reader Preference Measurement

Data Challenges and Robustness Checks	Method Employed
Incorporating heterogeneity among readers Impact of price-levels on plan preferences and attribute importances	A-priori segmentation Deployed two versions of the survey with different price levels and then employed a nonparametric Kolmogorov-Smirnov test to verify difference in plan preferences
Latent effect of usage situations during choice tasks Order effects resulting from choice task presentation Design efficiency (validating minimal overlap, orthogonality and level balance) Managerial relevance of choice tasks	Included interactions between design attributes Randomized choice tasks between respondents and versions Used OPTEX macro to obtain partial factorial design. The D and A efficiencies were maximized Imposed design constraints to produce meaningful plans and pretested the survey on employees at the collaborating newspaper to obtain face validity
Incentive compatibility Subject identification	An incentive-aligned conjoint design was adopted Random stratified sampling with strict screening procedures were adopted and respondents were recruited from two sources
Validating heterogeneity between segments' preferences	A Kruskal-Wallis 1-way ANOVA nonparametric test for k samples was performed on the levels of the design attributes between segments
Cognitive load Ballot-stuffing	Patterns in median response times Evaluation of IP address, browser information, operating system on the respondents' device and the response time
Straight-lining and acquiescence Predictive capability Extreme response behavior among subjects	Variance in response blocks Out of sample predictions Censoring on the left tail of the distribution and interquartile deviation criterion to identify outliers on the right tail of the distribution

Web Appendix W5: Descriptive Analyses of Transaction Data

Descriptive Statistics

	N	Mean	SD	Minimum	Maximum
1. ln(Print subscription volume)	108	13.55	0.10	13.27	13.70
2. ln(Print ad revenue)	108	16.59	0.27	15.81	16.92
3. ln(Online visitors in DMA)	108	12.82	0.14	12.44	13.10
4. ln(Online ad revenue)	108	13.50	0.74	12.05	14.50
5. ln(Newsroom investments)	108	14.76	0.14	14.37	14.95
6. ln(Distribution investments)	108	15.09	0.13	14.69	15.37
7. ln(Salesforce investments)	108	14.54	0.20	14.16	14.95
8. ln(Print potential)	108	15.36	0.04	15.25	15.41
9. ln(Online potential)	108	14.79	0.08	14.64	14.93
10. Print penetration (in %)	108	34.79	2.62	29.08	40.43
11. Online penetration (in %)	108	13.96	1.19	10.95	16.74

Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11
1. ln(Print subscription volume)	1.00										
2. ln(Print ad revenue)	0.81	1.00									
3. ln(Online visitors from NDMA)	-0.64	-0.42	1.00								
4. ln(Online ad revenue)	-0.61	-0.22	0.80	1.00							
5. ln(Newsroom investments)	0.56	0.74	0.00	0.15	1.00						
6. ln(Distribution investments)	0.71	0.78	-0.34	-0.21	0.77	1.00					
7. ln(Salesforce investments)	-0.29	0.18	0.54	0.78	0.48	0.23	1.00				
8. ln(Print potential)	0.77	0.83	-0.33	-0.21	0.72	0.70	0.08	1.00			
9. ln(Online potential)	-0.90	-0.68	0.85	0.78	-0.34	-0.62	0.44	-0.63	1.00		
10. ln(Print penetration)	0.93	0.65	-0.69	-0.72	0.36	0.57	-0.44	0.50	-0.88	1.00	
11. ln(Online penetration)	-0.23	-0.06	0.88	0.62	0.32	-0.01	0.49	0.03	0.50	-0.33	1.00

Note: $|r| > 0.20$, $p < 0.05$

Web Appendix W6-A: A Summary of Data and Modeling Challenges Encountered while Analyzing Transaction Data

Data/Modeling Challenge	Description of the Challenge	Method Employed to Verify the Challenge	Results
Model specification	Are the error terms contemporaneously correlated across equations?	Hausman specification test	Estimates obtained using SUR are systematically different from those obtained using the OLS
Serial correlation	Is there inter-temporal correlation within error terms?	Durbin Watson (DW) statistic	DW of the final model is acceptable and doesn't indicate serial correlation
Forecast accuracy	Does the estimated model exhibit high forecast accuracy?	Mean Absolute Prediction Error (MAPE) and Mean Absolute Deviation (MAD)	The final model has the lowest MAPE and MAD values
Unit roots in errors	Are the error terms evolving?	Phillip-Perron (PP) test on error terms	PP test indicates all four error terms are stationary
Unobserved heterogeneity	Is there unobserved heterogeneity?	Jacobson (1990) lagged error test	The lagged error terms in all 4 equations were significant indicating the presence of and need to account for unobserved heterogeneity
Exogeneity	Are the marketing-mix variables exogenous?	Engel, Hendry and Richard's test of exogeneity	All marketing mix investments were found to be weakly exogenous
Trend	Do the dependent variables exhibit trend?	Augmented Dicker Fuller test on dependent variables	All dependent variables exhibit trend
Year-end seasonality	Do the dependent variables exhibit seasonality?	A dummy variable was used to check year end seasonality (November and December month)	All dependent variables exhibit seasonality
Cyclicalilty	Do the dependent variables exhibit cyclicalilty?	Hodrick and Prescott filter was used to extract cyclicalilty in the dependent variables	All dependent variables exhibit cyclicalilty

Web Appendix W6-B: Checking for Exogeneity in the Market Response Model System

We test the exogeneity of newsroom investments (n), distribution investments (d) and sales force investments (s) using the Engle, Hendry and Richard's (1983) exogeneity test. Let $p_1(R, RMM)$ represent the joint density of reader demand and marketing mix investments and $p_4(A, AMM)$ represent the joint density of advertiser demand and marketing mix investments, where

$$p_1(R, RMM) = p_2(R|RMM) * p_3(RMM) \quad (1)$$

$$p_4(A, AMM) = p_5(A|AMM) * p_6(AMM) \quad (2)$$

$p_2(R|RMM)$ is the conditional density of reader demand and reader specific marketing mix investments and $p_3(RMM)$ is the marginal density of reader specific marketing mix investments. Similarly, $p_5(A|AMM)$ is the conditional density of advertiser demand and advertiser specific marketing mix investments, $p_6(AMM)$ is the marginal density of advertiser specific marketing mix investments. According to Engle, Hendry and Richard (1983), a precise specification for marginal density is not necessary if the marketing-mix investment is weakly exogenous and no loss of efficiency occurs when the estimation is based on the conditional density (Sridhar et al. 2011). To test this, we first estimated the following marginal models:

$$\begin{aligned} \ln(n_t) = & \alpha_{0n} + \alpha_{1n}n_{t-1} + \alpha_{2n}\ln(PA_{t-2}) + \alpha_{3n}\ln(PR_{t-3}) + \alpha_{4n}\ln(OA_{t-4}) \\ & + \alpha_{5n}\ln(OR_{t-5}) + \varepsilon_{nt} \end{aligned} \quad (3)$$

$$\begin{aligned} \ln(d_t) = & \alpha_{0d} + \alpha_{1d}d_{t-1} + \alpha_{2d}\ln(PA_{t-2}) + \alpha_{3d}\ln(PR_{t-3}) + \alpha_{4d}\ln(OA_{t-4}) \\ & + \alpha_{5d}\ln(OR_{t-5}) + \varepsilon_{dt} \end{aligned} \quad (4)$$

$$\begin{aligned} \ln(s_t) = & \alpha_{0s} + \alpha_{1s}s_{t-1} + \alpha_{2s}\ln(PA_{t-2}) + \alpha_{3s}\ln(PR_{t-3}) + \alpha_{4s}\ln(OA_{t-4}) \\ & + \alpha_{5s}\ln(OR_{t-5}) + \varepsilon_{st} \end{aligned} \quad (5)$$

where, the appropriate lags for covariates in each equation (i.e., (n1, ... , n5), (d1, ... , d5), (s1, ... , s5)) were determined based on AIC and adjusted R-squared values (Sridhar et al., 2011). Subsequently, we saved the residuals from equations 3, 4 and 5 and then examined the correlations between these residuals and the relevant residuals in the conditional model (i.e., $(\tilde{\varepsilon}_{1t} \ \tilde{\varepsilon}_{2t} \ \tilde{\varepsilon}_{3t} \ \tilde{\varepsilon}_{4t})'$ from equation 10 in the manuscript). An insignificant correlation would indicate that the marketing-mix variable is weakly exogenous (Naik, Raman, and Winer, 2005).

Analysis indicated that newsroom investments, distribution investments and sales force investments are indeed weakly exogenous. Specifically, the correlation between ε_{nt} in equation 3 and $\tilde{\varepsilon}_{2t}$ in equation 10 (in the paper) was 0.02 (p = 0.86) and the correlation between ε_{nt} in equation 3 and $\tilde{\varepsilon}_{4t}$ in equation 10 (in the paper) was 0.17 (p = 0.08). Similarly, the correlation between ε_{dt} in equation 4 and $\tilde{\varepsilon}_{2t}$ in equation 10 (in the paper) was -0.07 (p = 0.48). Lastly, the correlation between ε_{st} in equation 5 and $\tilde{\varepsilon}_{1t}$ in equation 10 (in the paper) was 0.15 (p = 0.13) and the correlation between ε_{st} in equation 5 and $\tilde{\varepsilon}_{3t}$ in equation 10 (in the paper) was -0.04 (p = 0.66). The lack of statistical significance among correlations suggests that precise specification for marketing-mix variables is not necessary in equation 10 (in the paper). These results are consistent with previous research that modeled newspaper finances (Sridhar et al. 2011).

References

Engle, Robert F, David F Hendry, and Jean-Francois Richard (1983), "Exogeneity," *Econometrica*, 51 (2), 277-304.

Naik, Prasad A., Kalyan Raman, and Russell S. Winer (2005), "Planning marketing-mix strategies in the presence of interaction effects," *Marketing Science*, 24(1), 25-34.

Sridhar, Shrihari, Murali K Mantrala, Prasad A Naik, and Esther Thorson (2011), "Dynamic Marketing Budgeting for Platform Firms: Theory, Evidence, and Application," *Journal of Marketing Research*, 48 (6), 929-43.

Web Appendix W7: Computation Times

The number of machine instructions that a computer can execute in one second is commonly measured using ‘Million Instructions Per Second’ (MIPS). Assuming 1 iteration is equivalent to 1 instruction and the CPU and I/O bus speed are held constant, computational time (in minutes) can be determined using: $\frac{\sum_{k=1}^K \binom{J}{k} P^k}{(MIPS \times 60)}$. A standard Excel application, such as the one we developed, running on an Intel I-7 2.93 GHz processor with multi-threading is known to execute about 6.9 MIPS (Williams, 2011).

Table W2-1: Time taken to parse all Iterations using a Line Search Technique

				Million Instructions per Second (MIPS) processed by Excel Application					
				6000000	7000000	8000000	9000000	10000000	11000000
Plan Alternatives	Segments	Price Points	Number of iterations	Time taken to parse all alternatives (in minutes)					
59	1	10	590	0	0	0	0	0	0
59	2	10	171690	0	0	0	0	0	0
59	3	10	32680690	0	0	0	0	0	0
59	4	10	4583940690	13	11	10	8	8	7
59	5	10	5.05223E+11	1403	1203	1053	936	842	765
59	6	10	4.55627E+13	126563	108483	94922	84375	75938	69034
59	7	10	3.45706E+15	9602937	8231088	7202202	6401958	5761762	5237965

References

Williams, Charles (2011), " The XIPS Challenge – how fast does Excel calculate?," [available at <https://fastexcel.wordpress.com/2011/05/25/xips-excel-calculations-per-second/>].

Web Appendix W8: Starting Values for the Optimizer

Input Description	Corresponding Variable(s) in the Model	Starting Value from the Collaborating Newspaper
Total number of plan configurations	J	59
Availability of print and digital formats in plan configurations	λ_j^p, λ_j^o	Two separate arrays describing whether plan j contains print and digital formats
Number of segments	K	7
Total number of print readers per segment in the NDMA	N_k^p	(595439, 595439, 340251, 723033, 808096, 467845, 723033)
Total number of digital readers per segment in the NDMA	N_k^o	(426449, 426449, 243685, 517831, 578753, 335067, 517831)
Proportion of each segment in the newspaper's reader base	φ_k	(0.13, 0.13, 0.11, 0.18, 0.14, 0.08, 0.23)
Segment-level willingness to pay for all plan configurations	RP_{kj}	A 59x7 vector of WTP values
Market response model parameters	Variables in Equations (15) – (18)	Parameters estimates from econometric analysis. Values for variables in the response model correspond to the values in the last period in the dataset
Margins on advertising and reader revenues	M_a, M_{pr}, M_{or}	0.545, 0.077, 0.20

Web Appendix W9: Accounting for Uncertainty in Parameter Estimates and Willingness to Pay Values

We evaluated profit-maximizing menus under several different business models assuming *point estimates* in the market response model and average segment-level willingness to pay estimates. However, the uncertainty surrounding these point estimates could affect the menu outcomes. For example, using different starting values in the optimization framework could affect the number of plans in the menu, composition of plans in the menu and price of the plans offered in the menu, and any of these could subsequently affect the gross profit obtained by adopting the menu. These changes could raise doubts about the robustness of the findings. Therefore, evaluating the menu while accounting for uncertainty in starting values is crucial for the success of the decision aid in terms of obtaining buy-in from the managers and applicability of the model in the real-world.

In this section, we will reevaluate our findings from the previous section after accounting for uncertainty arising from two sources: (a) variance in the segment-level willingness to pay estimates, and (b) variance in parameter estimates in the market response model.

Variance in the Willingness to Pay Estimates

The segment-level willingness to pay estimates are essentially subjects' willingness to pay for various plan configurations *averaged* by segment. These mean estimates are point estimates that do not capture the variability of willingness to pay among the respondents. A manager may be interested in knowing this information because variance determines the risk involved in offering a plan at its mean price. Take for instance a plan *j* with high variance. A manager would be less certain about offering plan *j* at its mean price because she would have less confidence in the number of readers within a segment who will derive positive surplus from subscribing to plan *j* at that price. On the other hand, a manager would be more certain about

offering a plan m at its mean price if plan m exhibits smaller variance surrounding its mean willingness to pay because the probability of readers deriving positive surplus from subscribing to plan m at that price would be higher.

Therefore, to account for managers' risk preferences with respect to segment-level willingness to pay estimates, we added the following constraint to the proposed optimization model: $\sigma_{jk}^2 \leq \tilde{\sigma}^2$ where, σ_{jk}^2 is the variance of plan j within segment k and $\tilde{\sigma}^2$ is the risk level of the manager. We simulated the algorithm for various values of $\tilde{\sigma}^2$ and obtained profit-maximizing menu parameters. Table W9-1 demonstrates multiple characteristics of the profit-maximizing menu under various risk levels for the integrated business model. Several interesting observations can be made:

- (1) Profit-maximizing menus for all risk levels were *pure bundles* of 7 day + digital and Sunday + digital plans. This is consistent with the result obtained using point estimates.
- (2) The total gross profits increased with an increase in $\tilde{\sigma}^2$ (see Figure W9-1). This finding corroborates with the notion that high risk yields high reward. Additionally, total gross profits at all risk levels are still higher than those in any other alternative business model.
- (3) Gross profit from advertising remained constant for all risk levels. This is interesting because it demonstrates that there exists a portfolio of print + digital bundles from which the manager can choose from depending on her risk level, without affecting the demand from readers and gross profit from advertising.
- (4) Next, price dispersion (computed as maximum price – minimum price) among plans within the menu decreased as the risk decreased. This indicates that a manager will price the plans more similarly as she becomes more risk averse.

(5) Last, the average menu price also dropped as the risk level decreased. This confirms the belief that the likelihood of readers subscribing to lower priced print online bundles is higher than the likelihood of subscribing to higher priced print + online bundles.

In summary, this sensitivity analysis confirms that the general profit implications of adopting the Integrated business model are robust to variance in willingness to pay estimates.

Variance in Parameter Estimates in the Market Response Model

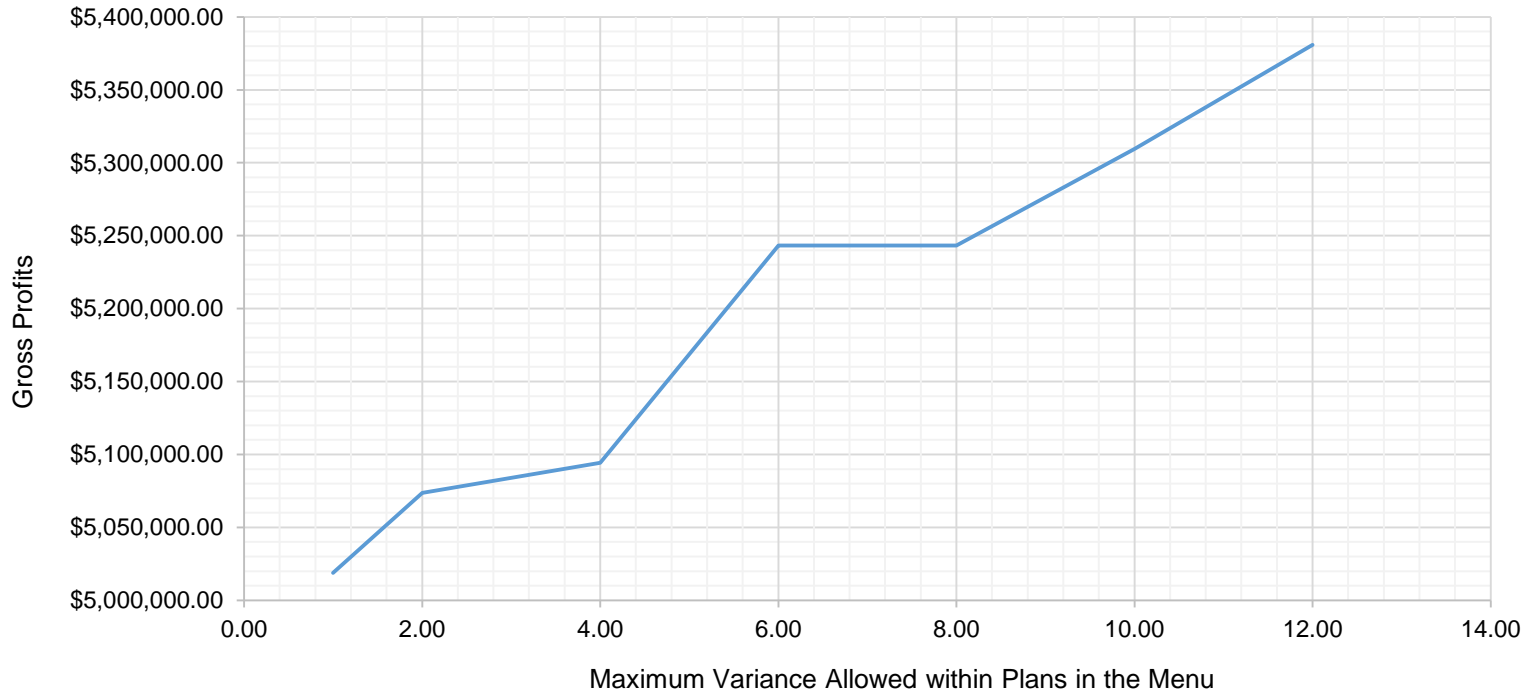
Another potential source of uncertainty, which is not in control of the manager, is the variance in parameter estimates of the market response model. Using point estimates in the optimization model assumes that the estimates are deterministic. In reality, there is uncertainty surrounding the point estimates, which will affect the profits obtained for a given menu offering.

To understand the menu and profit implications resulting from incorporating variance in parameter estimates, we adopted a boot-strapping approach. First, assuming that true parameters in the response model (in equations (32) through (36)) lie in the normal distribution $N(\beta, \delta)$, $\hat{\beta}$ was drawn from this distribution for each parameter in the response model. Subsequently, the algorithm was executed and the profits were retained. This procedure was repeated 100 times and the average profits were obtained for both Siloed as well as Integrated business models. While the profits varied in magnitude, the menu composition, plan prices and ranking of baseline, Siloed and Integrated business models with respect to profitability were remarkably consistent with the results obtained using the point estimates. Specifically, the average bootstrapped gross profits in the case of the Integrated business model were \$5,522,810.63 and those in the case of the Siloed business model were \$3,213,811.52.

Table W9-1: Menu Characteristics at Various Risk Levels under Integrated Business Model

Risk level	Total Gross Profits	Gross Profits from Advertising	Gross Profits from Circulation	Price Dispersion in the Menu	Average Price of Plans in the Menu
12.00	\$5,380,889.16	\$4,785,254.72	\$595,634.44	\$4.75	\$2.64
10.00	\$5,309,624.90	\$4,785,254.72	\$524,370.18	\$5.00	\$2.25
8.00	\$5,243,175.78	\$4,785,254.72	\$457,921.06	\$3.50	\$2.04
6.00	\$5,243,175.78	\$4,785,254.72	\$457,921.06	\$3.50	\$2.04
4.00	\$5,094,387.55	\$4,785,254.72	\$309,132.83	\$3.75	\$1.32
2.00	\$5,073,682.39	\$4,785,254.72	\$288,427.67	\$1.50	\$1.36
1.00	\$5,018,789.65	\$4,785,254.72	\$233,534.93	\$1.25	\$1.11

Figure W9-1: Risk and Return under Integrated Business Model



Web Appendix W10: Comments from Managers concerning the Results

The proposed model and accompanying decision tool were received with great enthusiasm by the collaborating newspaper. Following excerpts from our email communication with the executives at the collaborating firm demonstrate the relevance and impact that this research has had on the firm's overall strategy and bottom line and the firm's willingness to partake in model extensions and future research:

Marketing Manager A at the collaborating firm: *“The findings were so important to the paywall decision in developing our print-digital pricing. As we move forward, we look to work with you to improve these methodologies”*

Marketing Manager B at the collaborating firm: *“We continue to focus on optimizing digital subscriptions. With your previous insights, we've been diligent on pricing digital to enhance the perceived value of print and to not undercut print subscriptions”*